Advances in Spatial Science

Karima Kourtit
Peter Nijkamp
Robert Stimson *Editors*

Applied Regional Growth and Innovation Models

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Karima Kourtit • Peter Nijkamp • Robert Stimson
Editors

Applied Regional Growth and Innovation Models

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Editors
Karima Kourtit
Peter Nijkamp
Department of Spatial Economics
VU University
Amsterdam
Netherlands

Robert Stimson
University of Melbourne
Architecture Building
Parkville, VIC
Australia

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Preface

For 15 years already, each year the Tinbergen Institute in Amsterdam has been hosting a 2-day workshop that brings together by invitation about 25 regional scientists from around the world who are a mix of senior scholars and younger scholars, including graduate students, to present papers on a theme that relates to regional development. The workshops are overseen by Peter Nijkamp, Roger Stough and Robert Stimson and are organised out of the Department of Spatial Economics at the VU University in Amsterdam. Occasionally a second workshop has been held at George Mason University in the USA and at The University of Queensland in Australia.

The objective of the annual Tinbergen Institute workshop is to provide a semi-formal forum for a small group of regional scientists to come together to present cutting-edge research on theory, methods and empirical analysis on a specific theme in regional development, with an emphasis typically on the quantifying roles of human capital, creativity, knowledge, innovation, entrepreneurship, social capital and other endogenous factors in regional development. The workshop format allows for vigorous discussion and critique and fosters the development of future collaborations. While most of the participants in the workshops tend to come from Europe and the USA, it is common to invite participants from Australia, Asia and Latin America as well.

Following the workshops, selected participants are invited to revise their papers and submit them for consideration for publication, which always involves a professional review process. The workshop overseers and organisers form small groups to edit a collection of the papers from one or more of the workshops around a relatively specific theme. Over the years, a large number of publications have come out of the workshops in the form of edited books and special issues of leading academic journals, reflecting the high quality of the Tinbergen Institute workshops which have gained worldwide recognition among regional scientists in many countries. This book is such a product.

The chapters in this volume are based on a selection of the papers presented at the Tinbergen Institute workshops during the last few years that have been revised for this volume. The chapters have been through a careful screening and review process.

The broad theme addressed is reflected in the title *Applied Regional Growth and Innovation Models*, with a major emphasis on quantitative research methods. In an introductory chapter to the volume, the editors provide some background on the notion of space in action and action in space, especially within the context of endogenous regional development. They summarise the key issues that may be derived from the collection of chapters that relate to the themes addressed in the three parts of the book: Part I, which includes four chapters that focus on knowledge and innovation in space; Part II, which includes four chapters that relate to human capital and regional growth; and Part III, which includes five chapters that address spatial systems and economic development.

Across the 13 chapters, there is an explicit emphasis on the methodology as well as tools and techniques – both standard and innovative – that regional scientists employ in investigating these themes. The contributions to the book demonstrate empirical analysis at a variety of spatial scales at which modelling is conducted. This book contains a mixed focus on theoretical and methodological issues as well as a rich array of situational and time–space empirical contexts across a variety of spatial scales.

Amsterdam, The Netherlands Karima Kourtit
Amsterdam, The Netherlands Peter Nijkamp
Parkville, Australia Robert Stimson
May 2013

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Chapter 1
Editorial Introduction: Space in Action: Action in Space

Peter Nijkamp, Karima Kourtit, and Robert Stimson

1.1 Prologue

In recent years we have observed an avalanche of studies in regional growth and innovation. Numerous articles and books have addressed the driving forces of innovations and their impact on regional development. There is clearly a variety of approaches, ranging e.g. from shift-share analyses to theoretically-instigated spatial equilibrium analyses. Geographical scale levels appear to differ as well: we observe micro-based (individual) research and meso-modelling efforts.

The present volume on '*Applied Regional Growth and Innovation Models*' offers a new complement to the wealth of literature by zooming in on advanced quantitative-statistical and econometric tools that may be used to get a more appropriate understanding of the complexities of spatial dynamics, from the perspective of regional growth and innovation. Clearly, there is not a single and uniform tool box. On the contrary, we observe a broad spectrum of sophisticated analytical tools that are suitable for evidence-based research in regional science.

The present volume contains three interlinked parts:

A. Knowledge and Innovation in Space
B. Human Capital and Regional Growth
C. Spatial Systems and Economic Development.

P. Nijkamp (✉) • K. Kourtit
Department of Spatial Economics, VU University Amsterdam, De Boelelaan 1105, 1081 HV Amsterdam, The Netherlands
e-mail: p.nijkamp@vu.nl; k.kourtit@vu.nl

R. Stimson
Faculty of Architecture, Building and Planning, Australian Urban Research Infrastructure Network, University of Melbourne, 3010 Parkville, VIC, Australia
e-mail: rstimson@unimelb.edu.au

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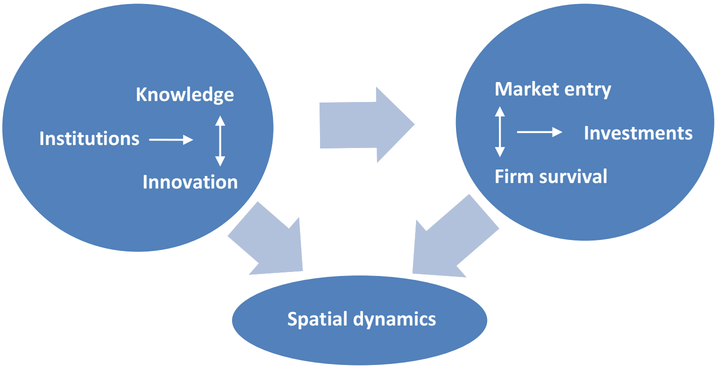

Fig. 1.1 The force field of knowledge and innovation in space

These three parts will now concisely be discussed, where we will make use of a so-called '*content cloud*'. A '*content cloud*' is a visual representation of the key concepts used in a scientific text, with a view to the identification – in a structured and often multi-colour way on the basis of hierarchical decompositions – of core messages measured through the relative frequencies of these concepts.

1.2 Knowledge and Innovation in Space

In the modern information and knowledge economy, the creation, diffusion, access and use of information and knowledge are key to a high long-term performance of actors – including regions – in a complex space-economy. In the context of open innovation systems, a matching of the supply of and the demand for knowledge (including industrial R&D) is a sine qua non for meeting the conditions of a competitive economy. The same also holds for institutional support frameworks that prompt entrepreneurship and innovative behaviour.

The synergetic combination of knowledge, innovation and institutional support stimulates the economic performance of regional actors, in particular, through a high market entry rate, new investments (including FDIs) and, in general, high firm survival rates.

The interlinked interfaces of the above sketched force fields lay the foundations for spatial dynamics of the space-economy, including the creation of new jobs and other signs of economic progress (see Fig. 1.1).

The force field sketched out in Fig. 1.1 is addressed in various applied modelling studies in Part A of the present volume. We will now offer a brief summary of each of the chapters in Part A.

Chapter 2, written by Michael Wyrwich, analyses the implications of knowledge-intensive firms in a regional system. This study investigates regional sources of entrepreneurial opportunities for knowledge-intensive start-up activities. The question is addressed whether or not it makes a difference if a knowledge-intensive industry is newly emerging as opposed to being well established. To this end, knowledge-intensive business services (KIBS) in East and West Germany are analyzed. At the time of German reunification in 1990, nearly no KIBS sector existed in the former socialist East Germany, in contrast to the western part of the country, where it had a much longer time to develop. The findings of this study reveal that growth of regional knowledge affects KIBS start-up activity in West Germany positively. There is no such effect for the East German region which was marked by heavy economic restructuring and decline over the course of transition. Nevertheless, the local presence of (high-quality) manufacturing and its demand for services affected the co-location of new KIBS firms in East Germany. This result suggests that strengthening the industrial base in lagging peripheral regions could be a conduit for promoting start-up activity in knowledge-intensive industries and knowledge-based regional development.

The next applied modelling study is produced by Eric de Noronha Vaz, Teresa de Noronha Vaz and Peter Nijkamp. They address the institutional innovation system in Portugal. Over the past decades the amount of studies on innovation systems in this country has been massive, originating from the great interest of policy makers searching for a solid scientific background and technical support to find out the most adequate strategies for development. Although from different perspectives, most studies find that knowledge creation and innovation are the major drivers of spatial change and growth. But important issues, such as interactive behaviour and knowledge transfer, are underinvestigated. Clearly, within the above described framing context, there are still several unsolved problems requiring attention, such as rules, norms, conventions or shared practices that form national or regional patterns of interactions among institutions. These phenomena provide a basis for the dissemination of knowledge which promote innovations further. The present paper provides an effort to develop a methodology able to find out how innovation institutions are related to each other and how they create networks of innovation. Although these two questions have been at the core of the innovation literature, addressed from various angles and scientific fields (e.g. economic, sociological, strategic, and psychological), this work aims to clearly trace networks of innovation as physical forces and to promote a deeper understanding of such networks, by mapping out the existing relationships. The available database comprises an extensive set of Portuguese innovative firms, spatially identified and able to design graph-flows to understand where and how strong the links for innovation are in Portugal, and to analyze the respective level of concentration or dispersion. The authors employ a novel exploratory technique, based on a biplot analysis. A parallel evaluation of innovation policy in the country is also provided to detect if such innovation flows can supply the arguments to sustain the level of effectiveness of innovation systems in the country.

A next study, by Megha Mukim, addresses investment patterns. This paper studies the determinants of investor's location choices across countries, both developing and developed, to gauge the relative importance of investment climate vis-à-vis existing FDI clustering. Using standardised data describing the institutional environment for FDI, the factors affecting new investments made in 2010 are

Fig. 1.2 A '*content cloud*' of Chaps. 2, 3, 4 and 5

addressed. The empirical analysis is carried out using count models and conditional logit models. The findings indicate that cumbersome start-up procedures don't deter investors, that better access and availability of land information increases the odds of new investments, and that the strength of arbitration systems has different implications in different regions. The effect of existing agglomerations on FDI is also very resilient. The author concludes that public policy may play a positive role in improving institutions if they were interested in attracting more FDI.

The final paper in Part A, written by Alexandra Tsvetkova, Jean-Claude Thill and Debbie Strumsky, addresses externalities in innovation. Extensive literature argues that knowledge spillovers are likely to be present in agglomerated regions with greater accumulated stock of knowledge. According to this view, firms exposed to knowledge spillovers should become more innovative and productive. Empirical research consistently finds a negative relationship between innovation and productivity, on the one hand, and the probability of exit, on the other. The authors test this supposition using non-parametric survival analysis. The chapter investigates the effects of metropolitan innovation on survival chances of stand-alone non-patenting firms in computer and electronic product manufacturing and healthcare. On average, computer and electronic product manufacturing firms tend to exit sooner in more innovative environments, while the opposite holds true for healthcare establishments. These results, however, are sensitive to a number of metropolitan characteristics.

It may now be interesting to explore the key concepts used in these four studies from an integrated perspective. In other words, which concepts are shared the most by all four chapters? And therefore, we will employ the above-mentioned '*content cloud*' analysis (see Fig. 1.2).

It is interesting to note that key terms from business life (like investments, firms, market, sector, innovations, companies) show up in a dominant way. But also supporting phenomena (like location, regions, knowledge, density) appear to boost a high presence. Apparently, the blend of private sector concepts and general overhead concepts assumes a prominent place in Part A.

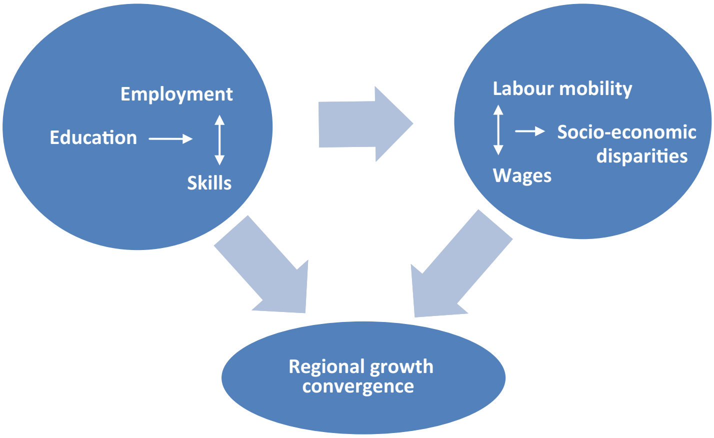

Fig. 1.3 The force field of human capital and regional growth

1.3 Human Capital and Regional Growth

The human factor in economic growth policy is an essential but often underresearched issue. The attention is often focused on job creation (as an output), while at the forefront of the regional development process human capital as an overarching input need is sometimes neglected. Employment is thus a critical factor, but not only in terms of volume, but more importantly in terms of qualifications (skills). To that end, the educational system is also a central success factor.

Favourable human capital conditions attract not only firms, but also domestic and international labour migrants. The influx of human capital into a region will have implications, not only for the labour market, but also for the wage levels in the area concerned. The ultimate result may be a transition towards a new socio-economic profile of the region concerned, including implications for spatial disparities.

The interdependencies in the above sketched force field are mapped out in Fig. 1.3, which highlight the drivers of convergence and divergence in a spatial-economic system.

The force field mapped out in Fig. 1.3 forms the cornerstone of various modelling applications in Part B of this volume. This part contains also four quantitative research studies. The first paper, written by Uwe Blien, Uwe Blien, Lutz Eigenhüller, Markus Promberger and Norbert Schanne presents an outline of the so-called shift-share regression and an application of this method to the analysis of employment development in Germany. The method is not a deterministic decomposition like the classical shift-share analysis, but a flexible econometric tool appropriate to test theory-related hypotheses. In this particular case, the effects of industry, firm size, wage, and qualification structures are tested. The aim of the study is the assessment of the determinants of employment development in the regions of the German Federal State Bavaria and the identification of regional fixed effects.

The next study employs also shift-share methods. The authors, Valente Matlaba, Mark Holmes and Philip McCann and Jacques Poot, combine classic and spatial shift-share decompositions of 1981–2006 employment change across the 27 states of Brazil. The classic shift-share method shows higher employment growth rates for underdeveloped regions that are due to an advantageous industry-mix and also due to additional job creation, commonly referred to as the competitive effect. Alternative decompositions proposed in the literature do not change this broad conclusion. Further examination employing exploratory spatial data analysis (ESDA) shows spatial correlation of both the industry-mix and the competitive effects. Considering that until the 1960s economic activities were more concentrated in southern regions of Brazil than they are nowadays, these results support beta convergence theories, but also find evidence of agglomeration effects. Additionally, a very simple spatial decomposition is proposed that accounts for the spatially-weighted growth of surrounding states. Favourable growth in northern and centre-western states is basically associated with those states' strengths in terms of a potential spatial spillover effect and a spatial competitive effect.

The next paper, written by Fabian Böttcher, Friso Schlitte, Annekatrin Niebuhr and Javier Revilla Diez, addresses increasing inequality in qualification-specific employment prospects that characterises labour markets in most highly developed countries. Theoretical models suggest that in-plant skill segregation might matter for the polarisation of employment and wages. According to these models, production technology and the educational level of the work force are important determinants of skill segregation. There are some studies that investigate the increasing in-plant skill segregation at the national level. However, since production technologies and skill structures are characterised by pronounced regional disparities, there are likely significant differences in the level of segregation between regions. But empirical evidence on corresponding regional inequalities is lacking. The objective of this analysis is to investigate regional disparities in skill segregation in Germany. The findings point to marked disparities among German regions. Moreover, the authors analyse the determinants of these differences at the regional level. The results of a regression analysis indicate that the local endowment with human capital is an important determinant for the regional level of skill segregation. Furthermore, skill segregation is increasing in most areas during the period under consideration, which may lead to unfavourable labour-market conditions for low-skilled workers in corresponding regional labour markets.

The final paper in Part B is written by Sarah Jewell and Alessandra Faggian. The authors analyze the migration behaviour of graduates from UK universities with a focus on the salary benefits they receive from the migration process. We focus on sequential interregional migration and specifically examine the case of STEM and creative subject graduates. Our analysis differs from previous studies in that it accounts explicitly for migrant selectivity through propensity score matching, and it also classifies graduates into different migration behaviour categories. Graduates were classified according to their sequential migration behaviour, first from their pre-university domicile to university and then from university to first job post-graduation. The results show that 'repeat migration', as expected, is associated with

Fig. 1.4 A '*content cloud*' of Chaps. 6, 7, 8 and 9

the highest wage premium (around 15 %). Other migration behaviours are also advantageous, although this varies across different types of graduates. Creative graduates, for instance, do not benefit much from migration behaviours other than repeat migration. STEM graduates, on the contrary, benefit from both late migration and staying in the university area to work.

The '*content cloud*' related to Chaps. 6, 7, 8 and 9 of Part B is presented in Fig. 1.4. This figure reveals interesting features. Concepts like skills, firms, growth, segregation, business, group migration, metropolitan, labour etc. appear to be present rather prominently. These are clearly the key terms used in the analysis of human capital in relation to regional growth.

1.4 Spatial Systems and Economic Development

Regional actors, cities and regions are not operating in a 'prison economy'. They interact with other entities in an open space-economy. A regional system makes up an interlinked set of open small economies. The performance of these regions is often measured in terms of growth and distribution of income. But income is generated – with different degrees of success – in different sectors, such as high-tech sectors, banking & finance etc. Thus, the sectoral composition and structure is also decisive for the relative performance of a region in an open system. Similarly, local business environments provide another supporting condition for high-performing regional economies.

The above-mentioned ramifications of drivers of spatial-economic performance have immediate spatial implications for the behaviour of all actors involved. First, competition may promote alliances in terms of business strategies, or at least

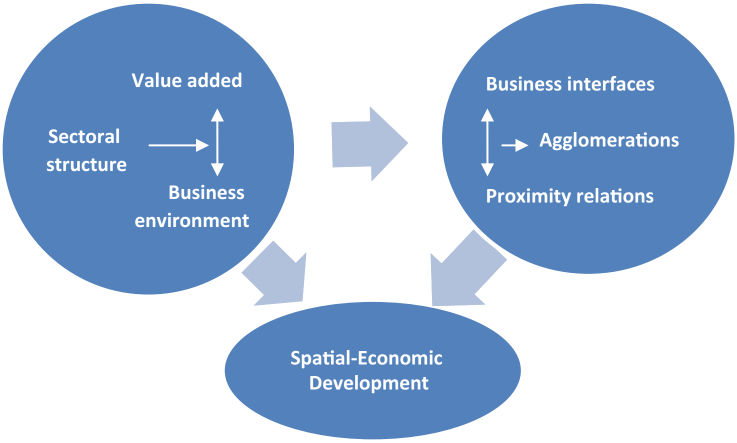

Fig. 1.5 The force field of entrepreneurship and spatial development

business interfaces driven by a joint interest. They may also encourage spatial interdependencies, which may manifest themselves in the emergence of spatial proximity relations, or in the ultimate case as agglomeration forces leading to urban concentration of activities. This set of forces is described in Fig. 1.5.

The ingredients of Fig. 1.5 will now be highlighted in more detail. The first chapter in Part C is a product of Stilianos Alexiadis, Konstantinos Eleftheriou and Peter Nijkamp. Their study examines the empirics of income convergence across the US States (1929–2005). Following the relevant literature, the empirical assessment is conducted using cross-section and time series data. Given the plethora of cross-section studies, the paper is focused mainly on a time series analysis. In particular, the approach advocates and implements an Error-Correction-Model (ECM) to assess the possibilities of *intra*regional convergence towards steady-state equilibrium, approximated in terms of the State with the highest per-capita income in each Bureau of Economic Analysis (BEA) region. In this way the hypothesis of regional convergence is examined in a more detailed way. The empirical analysis provides considerable support to the validity of the ECM.

The next study is pursued by Suzanne Kok. The current triumph of cities is often associated with the clustering of smart people in cities. This paper analyses whether this triumph relies on the presence of smart people (human capital) or (also) on the communication and interactions between these smart people. She measures the returns to communication in US cities in 2000. By estimating a simple wage model she finds find that the performance of communication tasks in cities raises, conditional on individual, occupational and city characteristics, wages substantially. The price of communication tasks increases with city size and with skill level. These findings are robust over several specifications, including instrumented variables. High-skilled workers cluster in large cities and communication-intense occupations. Her findings suggest that communication between these workers enhances additional productivity gains.

The notion of distance friction – or, reversely, proximity – is a central one in regional analysis. André Torre and Sofiène Lourimi present an interesting study on proximity relations among firms. Analysis of proximity relations has often focused on the areas of industrial relations and innovation, introducing successive refinements centred around various concepts of proximity. The aim of this article is to assess the respective role of spatial and non-spatial proximity relations, and local and long-distance links in innovative firms behaviours, using a representative case study. The authors explore the different proximity relations maintained by various types of innovative firms in a cluster, using an applied example, namely the optics cluster in the greater Paris region. In order to identify groups of firms, they apply Porter's analysis method to strategic groups. The results reveal the existence of four different groups of innovative firms that maintain specific spatial relations and mobilize local relations and long-distance exchanges in different ways, through mobility or ICT. Small innovative firms appear to be more constrained to permanent location, and the mobilization patterns of the different proximity types vary depending on the size of the firms, their place within the value chain, their degree of specialization and the maturity of the technology used.

Next, Karima Kourtit, Peter Nijkamp, Andrea Caragliu and Chiara Del Bo offer a multi-level modelling study on spatial capital and business performance. The firms' performance depends increasingly on the spatial economic context where firms are located. Because of the diffusion of advanced management techniques (e.g., total quality control), the relevance of the contextual conditions increases over time. Therefore, the type and quality of capital needed in the firm's production function crucially affects the firms' competitiveness on international markets. This study uses a novel micro data base of Dutch firms in knowledge and innovation-intensive industries in order to assess the relative importance of different forms of capital on the firms' business performance. Because of the different relevance of different forms of capital on different performance measures, the empirical modelling is carried out by means of multi-level analysis. Various evidence-based results are presented that show the relevance of 'spatiality' for the business performance of firms.

The final chapter in this volume, written by Patricio Aroca, Robert Stimson and Roger Stough, develops a structural equation model to analyze potential determinants of spatial variations in endogenous regional growth performance. Econometric approaches to analyzing spatial variation in regional economic performance typically use OLS regression models, often incorporating appropriate adjustments to account for the spatial autocorrelation problem inherent in using data sets based on arbitrarily demarcated de jure spatial units. The authors experiment with a structural equation model as an alternative approach to investigate potential determinants of spatial variation in the endogenous regional employment performance across functional economic regions in Australia. The dependent variable is a proxy measure of endogenous regional growth, namely the regional shift (differential) component derived from a shift-share analysis of change in employment in industry sectors standardized by the size of the labour force at the beginning of the period 1996–2006. Explanatory variables incorporate measures relating to a

Fig. 1.6 A '*content cloud*' of Chaps. 10, 11, 12, 13 and 14

range of factors that potentially influence endogenous regional economic performance (in particular, industry structure and industry specialization/diversification, population size and growth and income, and proxy measures for human capital, occupational structure, creative capital, social capital, and the location of a region in the national settlement system). Structural equation modelling helps address the measurement problem evident in the explanatory variables (otherwise giving biased estimators – the endogeneity problem) and the multi-collinearity problem inherent among them (making estimators unstable or non-robust), problems only partially addressed in procedures adjusting for endogeneity. Structural equation modelling separates these problems, providing a deeper insight into the structural nature of the relationships between explanatory variables that are significant in impacting on the outcome variable.

Next, we will present the '*content cloud*' associated with Chaps. 10, 11, 12, 13 and 14 of Part C (see Fig. 1.6).

Figure 1.6 shows that the key concepts here are: communication, proximity, firms, performance, convergence, specialisation, geographic, spatial and regional. It is clear that here the focus is more on concepts related to an open space-economy.

1.5 Regional Growth and Innovation in Perspective

Solid regional statistical and modelling experiments are necessary to map out the complex space-economy, in which innovation and regional growth play a central role. This volume comprises a set of such advanced quantitative studies. It highlights the importance of appropriate databases and tested empirical material.

Clearly, there is not a single and simple toolbox, but a great diversity of research tools that are needed to grasp the complexity of the space-economy. All these quantitative techniques have proven their operational meaning and practical relevance in the diversified set of cases presented in this volume. The set of methods discussed in this book is by no means exhaustive. But they all illustrate the wealth of current methodologies in regional innovation and growth research.

Part I
Knowledge and Innovation in Space

Chapter 2
Knowledge-Intensive Entrepreneurship Across Regions: Does Being a New Industry Make a Difference?

Michael Wyrwich

2.1 Introduction

Knowledge-intensive business services (KIBS) and especially non-technical professional KIBS firms fulfill a cross-divisional function in the knowledge-based development of economies and provide their clients customized, high-value services. Moreover, KIBS produce and diffuse knowledge and oversee markets. Their consultancy support helps firms to exploit their own knowledge potential (e.g., Miles et al. 1995; Muller and Zenker 2001; Wood 2002). Accordingly, understanding where and why KIBS firms locate is helpful in advising policy makers to foster the establishment of knowledge-intensive industries as a prerequisite to designing a knowledge-based economy.

Previous empirical work on location patterns of KIBS identifies local market size and regional sources of knowledge as determinants of location and new firm formation (e.g., Wood et al. 1993; Andersson and Hellerstedt 2009). However, prior research focused solely on data for established market economies where KIBS industries are in an advanced stage of development with respect to their distribution across space. But what if KIBS industries are newly emerging? Are the sources of opportunities for starting KIBS firms different? Understanding how KIBS start-up activity depends on context is of crucial relevance when it comes to policy implications. Policy makers in lagging regions that want to stimulate the emergence of KIBS industries might need other recipes than those ones that want to promote

I am indebted to Michael Fritsch and participants of the International Tinbergen Institute Workshop on "Innovation, Entrepreneurship and Regional Development" in May 2011 for helpful comments on earlier versions of this paper.

M. Wyrwich (✉)
Department of Economics and Business Administration, Friedrich-Schiller University Jena, Carl-Zeiss-Str. 3, 07743 Jena, Germany
e-mail: michael.wyrwich@uni-jena.de

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KIBS start-up activity in areas where the respective industries are already well-established.

This paper investigates whether regional sources of entrepreneurial opportunities in KIBS differ in an area where such industries are new to the region. Germany provides an intriguing two-territory "quasi-natural experiment" for such an analysis. In East Germany, the total KIBS sector was a newly emerging industry after the breakdown of communism 1989–1990, whereas in West Germany it had a much longer time to develop. Despite catching up processes after transition, many KIBS industries in East Germany are still underdeveloped which is identified as a stumbling block for regional development (Bechmann et al. 2010).

The empirical results suggest that the co-location of (high-tech) manufacturing has a positive effect on professional KIBS (P-KIBS) start-up activity in East Germany, whereas there is no such effect for the western part of the country. The finding for East Germany suggests that strengthening the industrial base in peripheral regions like East Germany might provide entrepreneurial opportunities for starting KIBS firms, which, in turn, might be an important channel for promoting knowledge-based regional development. The results for West Germany reveal a crucial role of the growth of regional knowledge for start-up activity in P-KIBS industries.

The remainder of this paper is as follows: First, a framework is presented in which regional determinants of KIBS locations are discussed in more detail (Sect. 2.2). Second, the empirical strategy is described (Sect. 2.3). Third, the findings of a regression analysis are discussed (Sect. 2.4). The last section concludes the paper (Sect. 2.5).

2.2 Regional Determinants of KIBS Location and Start-Up Activity

KIBS purchase knowledge, equipment, and investment goods from manufacturers and service firms (Miles et al. 1995). KIBS are referred to as "brokers of knowledge" (Muller and Zenker 2001) and "bridges for innovation" (Czarnitzki and Spielkamp 2003). They oversee market characteristics such as customer preferences and business solutions (Andersson and Hellerstedt 2009). Accordingly, KIBS firms combine new knowledge – gained from interactions with clients – with existing knowledge to develop customized services to better meet the clients' needs (Bettencourt et al. 2002; Wood 2002).

In regard to KIBS locations, strong regional differences can be detected. KIBS typically concentrate in metropolitan areas (Wood et al. 1993). Keeble and Nachum (2002) claim that KIBS tend to do so because of access to localized tacit knowledge and the need to access interregional and global networks, clients, and knowledge. Wood (2002) also stresses these urban advantages. Therefore, urban-based business activities may benefit from an extra-regional (international) demand for their services. Moreover, the benefits of interactions with clients are highest in metropolitan areas due to the conjunction of commercial, manufacturing, trading, business, and consumer as well as public sector activities. Knowledge spillovers stemming from these interactions might lead to the detection of entrepreneurial opportunities and KIBS spin-offs (Wood 2005). Accordingly, the importance of regional market size and regional sources of knowledge was found to affect the spawning of entrepreneurship in the KIBS sector (Andersson and Hellerstedt 2009).

The sector structure of the local economy – the regional customer base – might also affect the location of KIBS. First of all, tertiary activities are claimed to be influenced by industrial sector location (Jennequin 2008). Co-location interdependencies can be assumed, especially between manufacturing and (advanced) producer services (for a detailed discussion, see Andersson 2006). However, previous research also suggests that business services are utilized to a high degree by nonmanufacturing industries (Goe 1990; Glasmeier and Howland 1994). Andersson (2006) finds by simultaneous equation modeling that closeness to manufacturing is not an explanatory factor for the location of producer services in Sweden. For KIBS, empirical evidence reveals that the local manufacturing sector has no effect on start-up activity (Andersson and Hellerstedt 2009).

Nevertheless, manufacturing industries (especially with a high intensity of R&D) are in need of KIBS in close proximity, for instance, to advance their product development and innovation activities (Makun and MacPherson 1997; Den Hertog 2000). So, if a local KIBS sector is initially lacking or underdeveloped, the local presence of a high-quality manufacturing sector may provide a peculiar “window of opportunity,” as there are only a few incumbent local KIBS firms from which business services can be obtained. This situation might make a co-location of new KIBS firms attractive or induces KIBS spin-offs from the manufacturing sector until the “carrying capacity” – provided by the demand of the local manufacturing sector – is not exceeded. Thus, it might be that the effect of the presence of local manufacturing is not mechanistic but context-specific. In this respect, comparing regional sources of KIBS start-up activity in East and West Germany in the 1990s allows an investigation of whether the co-location of manufacturing affects the spawning of KIBS under specific conditions.

West Germany was an established market economy around the time of German re-unification (Carlin 1994). Therefore, it is safe to assume that the drivers of KIBS start-up activity are similar to those found in the previously mentioned studies that analyze data from Western European countries. Thus, it is expected that market size and regional knowledge are the dominant drivers of new KIBS location. Similarly, it is likely that the local manufacturing sector has no effect on the emergence of new KIBS firms.

H1: Market size has a positive effect on start-up activity across KIBS industries in West Germany.

H2: Regional knowledge has a positive effect on start-up activity across KIBS industries in West Germany.

The drivers of KIBS start-up activity in East Germany might be much different since such industries did not exist before German re-unification. This pattern can be traced back to the socialist past. In the former German Democratic Republic (GDR), the service sector was underdeveloped, as the economy was focused strongly on manufacturing and business service activities were mainly integrated into the structure of state-owned enterprises. Moreover, the production of knowledge in the GDR was organized by the state and centrally planned (Fritsch and Werker 1999), and accordingly there was no need for knowledge brokers and bridges for innovation and therefore no market for KIBS. Furthermore, self-employment was allowed only in selected private service industries in the former GDR serving private consumer demands (Pickel 1992).

In the early 1990s the eastern part of Germany underwent a "shock transition" toward a market economy and the principles and paradigms of market economy took over (Brezinski and Fritsch 1995). This process was accompanied by a tremendous privatization and downsizing of the state-owned economy (e.g., Hau 1998). Next to this top-down privatization there was a bottom-up process of new business formation. Start-up activity was extremely high in the 1990s, as entrepreneurs had a "window of opportunity" due to low competition and the immediate availability of entrepreneurial opportunities that were absent in socialism (Fritsch 2004).

There have been at least two sources of opportunities for starting a KIBS firm. First, the "institutional shock" of introducing the regulatory framework of West Germany (Brezinski and Fritsch 1995) presumably created demand for legal services, consultancy support, and other business services. Second, since the organization of innovation activity followed the principles of those in market economies as described, for instance, by Muller and Zenker (2001), brokers of knowledge were presumably needed. Furthermore, the general service orientation of firms in market economies, which sharply contrasts with socialist planned economies (Johnson and Loveman 1995), certainly created a general demand for (knowledge-intensive) business services.

The local economy could not obtain knowledge-intensive services from already existing incumbent firms. Thus, there opened a peculiar "window of opportunity" for starting a KIBS firm in East Germany. The size of this window depends also on the size of the manufacturing sector under the assumption that manufacturing firms are important clients of KIBS like in established market economies (e.g., Jennequin 2008). Further, given that proximity to clients is important in transition economies as well, it is expected that the local manufacturing sector makes a co-location of new KIBS firms attractive. This effect should be more pronounced for those manufacturing industries where knowledge plays an important role.

H3: The local manufacturing sector has a positive effect on start-up activity across KIBS industries in East Germany.

H4: The quality of the local manufacturing sector has a positive effect on start-up activity across KIBS industries in East Germany.

Regional knowledge presumably played only a minor role for KIBS start-up activity in East Germany. The former socialist system of innovation was in dissolution and a lot of knowledge depreciated since the GDR followed different technological paths (e.g., Mayntz 1995; Fritsch 2004). This socialist legacy explains to some degree deficiencies and low productivity in regional innovation systems in East Germany (Fritsch and Slavtchev 2010). Furthermore, positive effects of local market size on KIBS start-up activity might be mediated by tremendous urban adjustment processes that were found to affect the general level of start-up activity in urban areas negatively (Wyrwich 2012). Altogether, the role of market size and regional knowledge for new KIBS formation in East Germany is rather ambiguous.

2.3 Empirical Strategy

Data on start-up activity in KIBS industries in East and West Germany is obtained from the German Social Insurance Statistics. It contains information on every German establishment with at least one employee required to pay Social Insurance (Fritsch and Brixy 2004). In the present analysis, the occurrence of a new establishment number is counted as a start-up if less than 20 employees worked in the establishment in the year of occurrence. Still, it cannot be fully determined whether subsidiaries of incumbent KIBS firms are counted. It might be the case that KIBS firms from West Germany opened establishments in East Germany after reunification. However, according to workflow analyses, less than 10 % of newly occurring establishments starting with less than 20 employees are likely to be subsidiaries of larger firms (Hethey and Schmieder 2010). Data on explanatory variables is obtained from the German Social Insurance Statistics as well as from the Federal Statistical Offices.

The empirical analysis focuses on professional KIBS (P-KIBS). P-KIBS industries comprise a large share of the total KIBS sector. The respective service firms offer legal services, advisory and auditing services, environmental services, training and general office services (Miles et al. 1995, pp. 29–30). Firms of P-KIBS industries are likely to be of a cross-divisional character and may therefore not be specific to regional industry (manufacturing) structures like KIBS firms that provide technology-oriented knowledge-intensive business services (T-KIBS).[1] This is a crucial advantage for the intended empirical analysis since the aim is measuring a general effect of manufacturing on entrepreneurial opportunities. Unfortunately, data on the NACE system of industry classification are not available for the period under analysis. The data is stratified in accordance to the German industry classification WZ1973, which does not perfectly match with the NACE system (for details regarding the WZ1973 industry classification, see Amend and Bauer 2005). Table 2.3 provides the definition of P-KIBS industries applied in this paper.

The period under analysis is from 1995 to 2000. Start-up activity in P-KIBS industries in East Germany in the early 1990s might have been affected by outsourcing processes in the course of privatizing the state-owned economy. New

[1] Example: one typical T-KIBS industry is "Architectural and engineering activities and related technical consultancy" (NACE2003-code: 742). If a region has a high employment share in construction, it seems likely that consulting civil engineers and architects co-locate.

establishments stemming from outsourcing of business services due to legal arrangements and political decisions cannot be disentangled from new firms in the data. However, the privatization process was almost completed by the end of 1994; therefore, any effect of privatization on P-KIBS start-up activity should be modest after 1994 (Hau 1998).

The analysis is on the level of NUTSIII-Regions, which are roughly comparable to US counties. There are 112 NUTSIII-regions in East Germany (excluding Berlin), which are used for the current analysis. West Germany is comprised of 326 NUTSIII-Regions. The much larger Planning Regions, which are large functional economic regions, are not used for analysis; they might be too large for measuring location attributes reasonably, as proximity to clients is important for P-KIBS. As a way to account for spatial autocorrelation, cluster-corrected standard errors on the Planning Regions level are integrated into the empirical analysis.

As the panel structure of the data is exploited, the total number of start-ups in the P-KIBS sector in a NUTSIII-region in a year is used as an indicator for start-up activity. This count variable has the advantage (compared to start-up rates) that it does not suffer from a pseudo-correlation with an independent variable partially captured by the denominator of the start-up rate (Fritsch and Falck 2007). The methods employed are fixed-effects Poisson (for technical details, see Wooldridge 1999; for an application in entrepreneurship research, see Boente et al. 2009) and, as a robustness check, negative binomial regression models (Hilbe 2007).[2] The main Poisson model has the following estimation equation where α_r represents region-fixed effects and λ the expected number of start-ups in region r in year t. The focus is on the role of local manufacturing, regional knowledge, and market size (see Table 2.4 for an overview of employed variables and their definitions).

$$E(Start-ups_{rt}|Manufacturing_{rt}, Knowledge_{rt}, MarketSize_{rt}, Controls_{rt}) = \lambda_{rt} = \exp(\alpha_r + \beta_1 Manufacturing_{rt} + \beta_2 Knowledge_{rt} + \beta_3 MarketSize_{rt} + \beta_4 Controls_{rt})$$

The effect of local manufacturing on the number of start-ups is measured by its employment share. The quality of the regional manufacturing sector is assessed by differentiating between R&D-intensive manufacturing, in accordance with the classification by Grupp and Legler (2000), and other manufacturing industries. For differentiating the (within) quality of R&D manufacturing, the share of highly skilled workers within the total R&D-intensive manufacturing employment is introduced in the analysis.

One problem is that the employment share provides no information about how firms organize their internal functional division of labor across space. The demand for KIBS might be larger in regions with more headquarters, for instance, measured by the share of employees working as managers in the region. So regions might have the same employment share, but a totally different occupational structure

[2] Only 8 out of 2,628 observations had no P-KIBS start-up in a respective year. Therefore, zero inflation is not an issue.

within this employment. In East Germany, there is a lack of headquarters and manufacturing firms are rather extended workshop benches of West German companies (at least in the 1990s) (Bechmann et al. 2010). Headquarters are supposedly more important drivers of demand for KIBS than other functional units of firms. Thus, the lack of headquarters in East Germany might mediate positive effects of local manufacturing on P-KIBS start-up activity. Data on the occupations are unfortunately not available on a disaggregated regional level for the investigated time span.

The role of regional knowledge is captured by proxies for the growth of the regional knowledge base. Knowledge spillovers stemming from the local manufacturing sector are modeled by the growth of the sector-specific highly skilled workforce. In regard to knowledge spillovers not stemming from manufacturing, the growth of highly skilled employment in the service and public sectors is included. The previously found concentration of P-KIBS in large markets is investigated by employing a Harris-type market potential function, which is a distance-weighted sum of population across regions (Redding and Sturm 2008). This sum is added to the local market size (population) for measuring intra- and extra-regional demand.[3]

It is controlled for the employment share of the local P-KIBS industries. This proxy accounts for the role of industry experience (market knowledge) for detecting entrepreneurial opportunities (Shane 2000). Regional development prospects are captured by previous employment growth. Year dummies are included as well in the analysis.[4] All independent variables (except year dummies) are lagged by 1 year to avoid a simultaneity bias.

2.4 Results

2.4.1 Descriptive Statistics

Mean comparison tests indicate that there are significant differences between East and West Germany for all independent variables (see Tables 2.5 and 2.6 for summary statistics). This can be certainly traced back to the East German transition and the fact that P-KIBS industries were newly emerging in the former GDR.[5]

[3] The role of employment density is also focused on an extended version of the main model that is presented in the Appendix (see Table 2.9).

[4] The year dummies control, among other things, for the fact that since 1999, establishments that employ only marginal workers (*geringfügig Beschäftigte*) also had to register.

[5] The growth of knowledge across sectors is becoming smaller on average in East Germany, which might be explained by the continuous migration of the highly skilled workforce due to unfavorable labor market prospects in East Germany (Hunt 2006).

The unfavorable regional development, for instance, is reflected by the much lower employment growth. The market potential and the population density are higher in West Germany. The employment share of manufacturing and the share of R&D-intensive manufacturing are much lower in East Germany which has certainly to do with the pronounced de-industrialization in the early 1990s (for details, see Burda and Hunt 2001).

The relatively low level of R&D-intensive manufacturing in East Germany might suggest that there is also a low demand for KIBS tuned to the needs of quality manufacturing. Thus, the demand could also be provided by incumbent KIBS firms from outside the region – for instance, from West Germany. This counters the argument that there was a "window of opportunity." Indeed, the correlation (see Tables 2.7 and 2.8) between the employment share in non–R&D-intensive manufacturing and new P-KIBS formation is significantly negative. Furthermore, there is no correlation between R&D-intensive manufacturing employment and P-KIBS start-up activity. One feature of the local manufacturing sector that is positively related to P-KIBS start-up activity is the share of highly skilled employees in R&D-intensive manufacturing.

Altogether, the correlations suggest that there is probably no unconditional effect of local manufacturing on P-KIBS start-up activity. This is however not surprising; P-KIBS are concentrated in larger cities, where typically the employment share of manufacturing is low. Indeed, the correlation matrix reveals that the regional market potential and the employment share of the P-KIBS sector are positively correlated with start-up activity. P-KIBS employment is concentrated in larger and more densely populated areas.[6]

2.4.2 *Regression Analysis*

The first set of models reveals that market size and the growth of knowledge has a significant positive effect on start-up activity in West Germany which is in line with hypothesis 1 and 2 (see Table 2.1). Market size seems also to affect start-up activity positively in East Germany. However, in contrast to West Germany, the growth of knowledge is not related to start-up activity. This might have to do with deficiencies in regional innovation systems in East Germany related to the transition process (e.g., Fritsch and Slavtchev 2010) that negatively affect the commercialization of knowledge spillovers via entrepreneurship. It might also indicate that regional knowledge is only a crucial source of entrepreneurial opportunities when the P-KIBS sector is in a later stage of development.

[6] Another Interesting descriptive finding is that there is no significant difference between East and West Germany for the start-up rate. Thus, P-KIBS start-up activity in post-socialist East Germany was not, on average, "naturally" higher due to catching-up processes after the transition.

Table 2.1 Main model: fixed effects (NUTSIII) count data models with clustered (planning region) robust standard errors

	Poisson		Negbin	
Start-ups in P-KIBS sector (count)	West	East	West	East
Manufacturing				
Emp Share Manufacturing	0.301	1.444**	0.0837	1.397**
	(0.510)	(0.667)	(0.506)	(0.670)
Market size				
Market Potential (Log)	5.354***	3.412***	5.240***	3.399***
	(0.817)	(1.217)	(0.931)	(1.235)
Knowledge				
Know Growth Non-Manufac	0.284***	0.209	0.193**	0.207
	(0.0789)	(0.146)	(0.0807)	(0.149)
Know Growth Manufac	−0.0392	0.067	−0.0427	0.0604
	(0.104)	(0.134)	(0.0896)	(0.137)
Controls				
Emp Share P-KIBS	−0.167	6.924	−0.309	6.482
	(1.679)	(6.39)	(1.668)	(6.842)
Emp Growth All	−0.111	−0.224	0.102	−0.217
	(0.335)	(0.344)	(0.316)	(0.353)
Observations	1,956	672	1,956	672
Number of kreis	326	112	326	112

Notes: Standard Errors in Parentheses (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$)/Data for Berlin are not employed. All models include year dummies. It is also controlled for NUTS III dummies in the negative binomial regressions. These dummies are the fixed panel variable in the Poisson models

The local presence of manufacturing has no effect on start-up activity in West Germany. This finding is in line with previous research for Western Europe on entrepreneurship across KIBS industries. The local manufacturing sector seems to provide no entrepreneurial opportunities where P-KIBS industries are already well developed. There is a significant positive effect of the local manufacturing employment on start-up activity in East Germany where P-KIBS industries were newly emerging. This finding is in line with hypothesis 3. Regional employment growth and the share of already existing P-KIBS firms have no effect on start-up activity.[7]

The second set of models investigates the role of the quality of the local manufacturing sector for P-KIBS start-up activity (see Table 2.2). The results show that the employment share of R&D-intensive manufacturing has a significant positive effect in East Germany. The higher the share of highly skilled employees within R&D-intensive manufacturing, the stronger is the positive effect. Thus, co-location of manufacturing seems to provide entrepreneurial opportunities in East Germany. This finding is in line with hypothesis 4. There is no effect for

[7] The local employment share of the P-KIBS has a significant positive effect on start-up activity in East and West Germany only when year dummies are not included in the analysis. Results can be obtained upon request.

Table 2.2 Main model with detailed assessment of local manufacturing

	Poisson		Negbin	
Start-ups in P-KIBS sector (count)	West	East	West	East
Manufacturing				
Emp Share R&D-Manufac	0.516	2.030**	0.315	1.988**
	(0.628)	(0.843)	(0.637)	(0.907)
Emp Know R&D-Manufac	0.547	1.996***	0.413	1.999***
	(0.604)	(0.740)	(0.633)	(0.756)
Emp Share Non-R&D-Manufac	−0.367	1.19	−0.519	1.161
	(0.657)	(1.025)	(0.680)	(1.015)
Market size				
Market Potential (Log)	5.442***	3.138**	5.232***	3.128**
	(0.836)	(1.262)	(0.971)	(1.286)
Knowledge				
Know Growth Non-Manufac	0.294***	0.213	0.204**	0.212
	(0.0807)	(0.152)	(0.0831)	(0.156)
Know Growth R&D-Manufac	−0.00442	−0.132	−0.00261	−0.135
	(0.0706)	(0.0884)	(0.0645)	(0.0919)
Know Growth Non-R&D-Manufac	−0.0109	0.0208	−0.00511	0.0192
	(0.0461)	(0.0788)	(0.0433)	(0.0811)
Controls				
Emp Share P-KIBS	−0.345	2.602	−0.455	2.372
	(1.605)	(6.39)	(1.582)	(6.726)
Emp Growth All	−0.184	−0.124	0.0237	−0.118
	(0.361)	(0.335)	(0.342)	(0.344)
Observations	1,956	672	1,956	672
Number of kreis	326	112	326	112

Notes: Standard Errors in Parentheses (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$)/Data for Berlin are not employed. All models include year dummies. It is also controlled for NUTS III dummies in the negative binomial regressions. These dummies are the fixed panel variable in the Poisson models

other manufacturing industries. So it seems that the quality of the local manufacturing sector matters. Further, there is no manufacturing effect in West Germany even when focusing on quality. The results on market size and regional knowledge are robust as well.

The results (with regard to the local presence of manufacturing and knowledge spillovers) do not change when introducing employment density as a control for proximity of the local market (see Table 2.9). The market potential is insignificant in this specification in both parts of the country, which might be explained (at least in West Germany) by the high correlation of both variables ($r = 0.5$). In East Germany, the effect of employment density is only weakly significant. Compared to West Germany there are no agglomerations, except for the Berlin region, which might explain the lower effect of density. The market potential variable in East Germany, in turn, seems to be driven by proximity to Berlin. Excluding regions adjacent to Berlin from the regression reveals that market potential becomes insignificant even without controlling for density (see Table 2.10). Thus, the effect of market potential seems to be smaller in East Germany, which probably has to do with the peripheral character of the eastern part of Germany.

Altogether, the results are in line with the proposed hypotheses. It seems that the local manufacturing sector indeed provides opportunities for starting a P-KIBS firm under specific conditions. Market size and knowledge matter especially when the regional distribution of P-KIBS industries is already established.

2.5 Concluding Remarks: What Can Be Learned?

KIBS firms provide their clients with customized high-value business services and help them to exploit their own knowledge potential. Employment and start-up activity in this knowledge-intensive sector is unevenly distributed across regions, which previous research could reasonably explain by the local market size and local sources of knowledge.

Research so far has only focused on the case where KIBS industries have already been established with respect to their development across space. It is, however, unclear which factors determine the emergence of KIBS industries when they are newly emerging in a certain territory. The aim of this paper was to fill this research gap by showing how sources of entrepreneurial opportunities in knowledge-intensive industries can differ across space when taking into account such a scenario. To this end, this study analyzed data on professional KIBS (P-KIBS) start-ups in the 1990s in East and West Germany. In the eastern part of the country (the former socialist GDR), no KIBS existed when the socialist system collapsed in 1989–1990. In West Germany, P-KIBS industries had developed over a much longer time period.

The results indicate that the presence of (high-quality) manufacturing has a positive effect on the level of P-KIBS start-ups in East Germany, whereas there is no effect of manufacturing in the western part of the country. The latter result is in line with previous findings for Western Europe. The distinct result for East Germany where P-KIBS industries were underdeveloped in the early 1990s indicates that the local manufacturing sector requires at least a critical amount of KIBS in close proximity. Thus, there seems to have been a "window of opportunity" for starting new P-KIBS firms at the beginning of transition. This window might close when the regional distribution of P-KIBS industries is rather established like in the case of Western Germany.

With respect to other regional conditions, it could be shown that the general market potential has had a positive effect on P-KIBS start-up activity in East Germany. This relationship is however much smaller than in West Germany. Regional knowledge spillovers have a positive effect on new P-KIBS formation in West Germany, whereas in the eastern part of the country there is no such effect.

This difference might have to do with deficiencies in the East German innovation system – which, in turn, negatively affect the commercialization of knowledge via entrepreneurship. The results on regional knowledge and market size might be driven by the socialist legacy of East Germany. Nevertheless, the paper provides insights on how regional sources of entrepreneurial opportunities can depend on institutional context and the stage of development of the industry with respect to its evolution across space.

One drawback of the analysis is that no information on the distribution of functionally different economic units of companies (headquarters vs. extended workshop benches) can be exploited in the period under analysis. The actual demand for KIBS from the local manufacturing might be affected by the way manufacturing firms organize their activities across space. The lack of information on this pattern is a limitation of the present research. However, spatial proximity to headquarters is presumably more important than location close to extended workshop benches. Given that East Germany is in short supply of the former, one can speculate that the positive effect of local manufacturing would have been even stronger if the functional composition of East German manufacturing were different.

The positive effect of the presence of local manufacturing employment in East Germany indicates that it might be the case that strengthening the industrial base in lagging peripheral regions is a conduit for fostering the emergence of P-KIBS industries, which itself might become an important source of knowledge-based regional development. This might be even more important in places like East Germany where regional knowledge and spillovers hardly induce the emergence of new P-KIBS firms. Promoting KIBS is presumably not a stand-alone policy. Rather it should be considered as part of a much wider regional policy toolkit. Furthermore, the findings suggest that policy concepts to foster knowledge-intensive entrepreneurship as a conduit of knowledge-based development should be tuned to specific regional conditions.

It is acknowledged that the sources of entrepreneurial opportunities might be different for technology-oriented KIBS which have not been investigated in this paper. Furthermore, it needs to be tested which factors drive the initial emergence of KIBS firms in other regions of the world. So, it would be interesting to analyze data on emerging economies and the Central Eastern European economies, where KIBS and knowledge-intensive entrepreneurship are still in a comparatively early stage of development. Which regional sources can be found there? What differences and similarities can be found compared to regions where the same industries are well established? Apart from that, an analysis of (historical) data from market economies and other institutional contexts is warranted to enhance our understanding of the emergence of knowledge-intensive industries across regions.

Appendix

Table 2.3 Definition of non-technical advisory ("professional") services (P-KIBS)

NACE	WZ1973	Description
7411	790	Legal activities
7412	791	Accounting, bookkeeping and auditing activities; tax consultancy

Notes: For details about the industry classification WZ1973, see Amend and Bauer (2005); for KIBS definition and classification, see Grupp and Legler (2000); the industries cannot be transcoded perfectly from the NACE system to the WZ1973

Table 2.4 Definition of variables

Variable	Definition
Start-ups P-KIBS	Number of new establishments
Start-up rate P-KIBS	Start-ups divided by population between 18 and 64
Know Growth Non-Manufac	Annual growth of employment holding a university degree (service and public sector)
Market Potential (Log)	Distance weighted sum of population in other regions + total regional population (Harris-type function)
Employment Density (Log)	Total employment divided by size in km^2
Emp Share P-KIBS	Share of employees in P-KIBS
Emp Growth All	Annual growth of total regional employment
Emp Share Manufacturing	Share of employees in manufacturing within total regional employment
Know Growth Manufac	Annual growth of employment in manufacturing holding a university degree
Emp Share R&D-Manufac	Share of employees in R&D-intensive manufacturing within total regional employment
Emp Know R&D-Manufac	Share of employees in R&D-intensive manufacturing holding a university degree
Know Growth R&D-Manufac	Annual growth of employment in R&D-intensive manufacturing holding a university degree
Emp Share Non-R&D-Manufac	Share of employees in non-R&D-intensive manufacturing within total regional employment
Know Growth Non-R&D-Manufac	Annual growth of employment in non-R&D-intensive manufacturing holding a university degree

Table 2.5 Summary statistics for East Germany

	Mean	Standard deviation	Minimum	Maximum	Median
Start-ups P-KIBS	18.391	21.033	0	214	13
Start-up rate P-KIBS	20.706	12.009	0	89.113	17.334
Know Growth Non-Manufac	0.992	0.106	0.65	1.842	0.985
Market Potential (Log)	12.915	0.188	12.406	13.653	12.929
Employment Density (Log)	3.85	1.219	2.148	6.965	3.554
Emp Share P-KIBS	0.011	0.004	0.003	0.032	0.01
Emp Growth All	0.983	0.047	0.787	1.298	0.98
Emp Share Manufacturing	0.241	0.072	0.067	0.446	0.247
Know Growth Manufac	0.961	0.103	0.487	1.512	0.959
Emp Share R&D-Manufac	0.085	0.043	0.016	0.313	0.076
Emp Know R&D-Manufac	0.126	0.062	0.009	0.456	0.116
Know Growth R&D-Manufac	0.971	0.172	0.315	2.5	0.96
Emp Share Non-R&D-Manufac	0.157	0.055	0.048	0.349	0.152
Know Growth Non-R&D-Manufac	0.975	0.176	0.433	3.449	0.969

Notes: N = 672. The mean values are significantly different than those in West Germany (except for the start-up rate)

Table 2.6 Summary statistics for West Germany

	Mean	Standard Deviation	Minimum	Maximum	Median
Start-ups P-KIBS	29.547	51.257	0	803	15
Start-up rate P-KIBS	20.133	16.456	0	125.5	14.91
Know Growth Non-Manufac	1.042	0.136	0.596	1.789	1.035
Market Potential (Log)	13.141	0.334	12.466	15.124	13.079
Employment Density (Log)	4.278	1.285	2.007	7.446	3.554
Emp Share P-KIBS	0.017	0.009	0.003	0.094	0.015
Emp Growth All	0.991	0.029	0.604	1.173	0.99
Emp Share Manufacturing	0.409	0.111	0.133	0.785	0.413
Know Growth Manufac	1.028	0.08	0.577	1.793	1.027
Emp Share R&D-Manufac	0.192	0.102	0.015	0.753	0.176
Emp Know R&D-Manufac	0.076	0.047	0.006	0.333	0.064
Know Growth R&D-Manufac	1.037	0.118	0.433	2.361	1.031
Emp Share Non-R&D-Manufac	0.217	0.083	0.029	0.544	0.216
Know Growth Non-R&D-Manufac	1.024	0.111	0.385	2.798	1.019

N = 1,956. The mean values are significantly different than those in East Germany (except for the start-up rate)

Table 2.7 Correlation matrix for East Germany

		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]
[1]	Start-up rate P-KIBS	1										
[2]	Start-ups P-KIBS	0.675***	1									
[3]	Know Growth Non-Manufac	0.042	0.032	1								
[4]	Market Potential [Log]	0.186***	0.590***	−0.144***	1							
[5]	Employment Density [Log]	0.539***	0.501***	−0.084**	0.234***	1						
[6]	Emp Share P-KIBS	0.629***	0.656***	−0.076**	0.288***	0.602***	1					
[7]	Emp Growth All	−0.219***	−0.132***	0.255***	−0.039	−0.286***	−0.187***	1				
[8]	Emp Share R&D-Manufac	0.035	−0.028	−0.084**	0.298***	0.081**	−0.052	0.001	1			
[9]	Emp Know R&D-Manufac	0.377***	0.404***	−0.037	0.339***	0.540***	0.375***	−0.195***	0.290***	1		
[10]	Know Growth R&D-Manufac	−0.061	−0.076**	0.015	−0.177***	−0.093**	−0.053	0.127***	0.002	−0.105***	1	
[11]	Emp Share Non-R&D-Manufac	−0.394***	−0.326***	−0.042	−0.025	−0.393***	−0.468***	0.100***	0.06	−0.255***	0.016	1
[12]	Know Growth Non-R&D-Manufac	−0.022	−0.029	−0.024	0.001	−0.089**	−0.06	0.148***	0.039	−0.069*	−0.057	−0.015

Notes: N = 672/Significance levels in parentheses (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$)

Table 2.8 Correlation matrix for West Germany

		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]
[1]	Start-up rate P-KIBS	1										
[2]	Start-ups P-KIBS	0.601***	1									
[3]	Know Growth Non-Manufac	0.466***	0.180***	1								
[4]	Market Potential [Log]	0.222***	0.618***	0.003	1							
[5]	Employment Density [Log]	0.348***	0.380***	−0.023	0.446***	1						
[6]	Emp Share P-KIBS	0.529***	0.527***	0.070***	0.386***	0.481***	1					
[7]	Emp Growth All	0.250***	0.108***	0.322***	−0.033	−0.166***	0.065***	1				
[8]	Emp Share R&D-Manufac	0.013	−0.02	0.029	0.069***	0.215***	−0.115***	−0.027	1			
[9]	Emp Know R&D-Manufac	0.433***	0.468***	0.046**	0.375***	0.542***	0.468***	−0.004	0.228***	1		
[10]	Know Growth R&D-Manufac	0.040*	−0.019	0.024	−0.117***	−0.154***	−0.073***	0.177***	−0.003	−0.054**	1	
[11]	Emp Share Non-R&D-Manufac	−0.367***	−0.309***	−0.018	−0.171***	−0.530***	−0.505***	0	−0.287***	−0.513***	0.055**	1
[12]	Know Growth Non-R&D-Manufac	0.055**	0.004	0.091***	−0.060***	−0.079***	−0.006	0.127***	−0.023	−0.037	−0.025	0.029

Notes: N = 1,956/Significance levels in parentheses (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$)

Table 2.9 Main model with additional control for employment density

	Poisson		Negbin	
Start-ups in P-KIBS sector (count)	West	East	West	East
Manufacturing				
Emp Share R&D-Manufac	0.203	2.003**	−0.0148	1.956**
	(0.610)	(0.837)	(0.613)	(0.902)
Emp Know R&D-Manufac	0.198	1.941***	0.116	1.942***
	(0.586)	(0.693)	(0.582)	(0.707)
Emp Share Non-R&D-Manufac	−0.405	1.137	−0.575	1.103
	(0.600)	(0.976)	(0.622)	(0.960)
Market size				
Market Potential (Log)	3.956***	2.813*	3.603***	2.782
	(0.957)	(1.653)	(1.111)	(1.696)
Employment Density (Log)	0.777**	0.139	0.775**	0.147
	(0.312)	(0.397)	(0.305)	(0.408)
Knowledge				
Know Growth Non-Manufac	0.319***	0.215	0.227***	0.214
	(0.0804)	(0.150)	(0.0821)	(0.154)
Know Growth R&D-Manufac	0.0127	−0.134	0.0118	−0.136
	(0.0715)	(0.0894)	(0.0658)	(0.0932)
Know Growth Non-R&D-Manufac	−0.0106	0.0215	−0.00516	0.0198
	(0.0475)	(0.0791)	(0.0437)	(0.0813)
Controls				
Emp Share P-KIBS	−0.674	3.486	−0.838	3.309
	(1.432)	(6.489)	(1.424)	(6.765)
Emp Growth All	−0.716	−0.197	−0.494	−0.195
	(0.447)	(0.429)	(0.421)	(0.439)
Observations	1,956	672	1,956	672
Number of kreis	326	112	326	112

Notes: Standard Errors in Parentheses (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$)/Data for Berlin are not employed. All models include year dummies. It is also controlled for NUTS III dummies in the negative binomial regressions. These dummies are the fixed panel variable in the Poisson models

Table 2.10 Main model for East German regions not adjacent to Berlin

	Poisson	Negbin
Start-ups in P-KIBS sector (count)	East	East
Manufacturing		
Emp Share R&D-Manufac	2.154**	2.104**
	(0.884)	(0.964)
Emp Know R&D-Manufac	2.112***	2.093***
	(0.747)	(0.749)
Emp Share Non-R&D-Manufac	1.386	1.354
	(1.166)	(1.163)
Market size		
Market Potential (Log)	1.461	1.439
	(1.984)	(2.018)
Knowledge		
Know Growth Non-Manufac	0.199	0.197
	(0.153)	(0.157)
Know Growth R&D-Manufac	−0.0726	−0.0765
	(0.0855)	(0.0906)
Know Growth Non-R&D-Manufac	0.046	0.0429
	(0.0840)	(0.0877)
Controls		
Emp Share P-KIBS	−1.851	−2.136
	(6.664)	(7.179)
Emp Growth All	−0.248	−0.241
	(0.330)	(0.340)
Observations	606	606
Number of kreis	101	101

Notes: Standard Errors in Parentheses (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$)/Data for Berlin are not employed. All models include year dummies. It is also controlled for NUTS III dummies in the negative binomial regressions. These dummies are the fixed panel variable in the Poisson models

References

Amend E, Bauer F (2005) Vergleichende Analyse von Länderarbeitsmärkten: Länderstudie Nordrhein-Westfalen, IAB regional Nr. 01/2005. IAB, Nordrhein-Westfalen

Andersson M (2006) Co-location of manufacturing & producer services: a simultaneous equation approach. In: Karlsson C, Johannsson B, Stough R (eds) Entrepreneurship and dynamics in the knowledge economy. Routledge, New York, pp 94–125

Andersson M, Hellerstedt K (2009) Location attributes and start-ups in knowledge-intensive business services. Ind Innov 16:103–121

Bechmann S, Dahms V, Fischer A, Frei M, Leber U (2010) 20 Jahre Deutsche Einheit: Ein Vergleich der west- und ostdeutschen Betriebslandschaft im Krisenjahr 2009, IAB-Forschungsbericht 6/2010. IAB, Nürnberg

Bettencourt LA, Brown SB, Ostrom AL, Roundtree RI (2002) Client co-production in knowledge-intensive business services. Calif Manage Rev 44:100–128

Boente W, Falck O, Heblich S (2009) The impact of regional age structure on start-up activity. Econ Geogr 85:269–288

Brezinski H, Fritsch M (1995) Transformation: the shocking German way. Moct-Most 5:1–25
Burda MC, Hunt J (2001) From reunification to economic integration: productivity and the labor market in Eastern Germany. Brook Pap Econ Act 2:1–92
Carlin W (1994) West German growth and institutions: 1945–1990, National Bureau of Economic Research working paper 896. NBER, Cambridge, MA
Czarnitzki D, Spielkamp A (2003) Business services in Germany: bridges for innovation. Serv Ind J 23:1–30
Den Hertog P (2000) Knowledge-intensive business services as co-producers of innovation. Int J Innov Manag 4:491–528
Fritsch M (2004) Entrepreneurship, entry and performance of new business compared in two growth regimes. J Evolut Econ 14(5):525–542
Fritsch M, Brixy U (2004) The establishment file of the German social insurance statistics. Zeitschrift für Wirtschafts- und Sozialwissenschaften 124:183–190
Fritsch M, Falck O (2007) New business formation by industry over space and time: a multidimensional analysis. Reg Stud 41(2):157–172
Fritsch M, Slavtchev V (2010) Determinants of the efficiency of regional innovation systems. Reg Stud. doi:10.1080/00343400802251494
Fritsch M, Werker C (1999) Systems of innovation in transition. In: Fritsch M, Brezinski H (eds) Innovation and technological change in Eastern Europe – pathways to industrial recovery. Elgar, Cheltenham/Brookfield, pp 5–22
Glasmeier AK, Howland M (1994) Service-led rural development: definitions theories and empirical evidence. Int Reg Sci Rev 16:197–229
Goe WR (1990) Producer services, trade and the social division of labour. Reg Stud 24:327–342
Grupp H, Legler H (2000) Hochtechnologie 2000. Fraunhofer Institute for Systems and Innovation, Karlsruhe/Hannover
Hau H (1998) Privatization under political interference: evidence from Eastern Germany. Eur Econ Rev 42:1177–1201
Hethey T, Schmieder JF (2010) Using worker flows in the analysis of establishment turnover – evidence from German administrative data, FDZ Methodenreport, 06/2010. IAB, Nürnberg
Hilbe JM (2007) Negative binomial regression. Cambridge University Press, Cambridge
Hunt J (2006) Staunching emigration from East Germany: age and the determinants of migration. J Eur Econ Assoc 4:1014–1037
Jennequin H (2008) The evolution of the geographical concentration of tertiary sector activities in Europe. Serv Ind J 28:291–306
Johnson S, Loveman GW (1995) Starting over in Eastern Europe: entrepreneurship and economic renewal. Harvard Business School Press, Boston
Keeble D, Nachum L (2002) Why do business service firms cluster? Small consultancies, clustering and decentralization in London and southern England. Trans Inst Br Geogr 27:67–90
Makun P, MacPherson AD (1997) Externally-assisted product innovation in the manufacturing sector: the role of location, inhouse R&D and outside technical support. Reg Stud 31:659–668
Mayntz R (1995) Sektorale Unterschiede in der Transformation des Wissenschaftssystems der DDR. Berliner Journal für Soziologie 4:443–453
Miles I, Kastrinos N, Flanagan K, Bilderbeek R, den Hertog P, Huntink W, Bouman M (1995) Knowledge-intensive business services: users, carriers, and source of innovation. PREST, Manchester
Muller E, Zenker A (2001) Business services as actors of knowledge transformation: the role of KIBS in regional and national innovation systems. Res Policy 30:1501–1516
Pickel A (1992) Radical transitions: the survival and revival of entrepreneurship in the GDR. Westview Press, Boulder
Redding SJ, Sturm DM (2008) The costs of remoteness: evidence from German division and reunification. Am Econ Rev 98:1766–1797
Shane S (2000) Prior knowledge and the discovery of entrepreneurial opportunities. Organ Sci 11:448–469

Wood PA (2002) Knowledge-intensive services and urban innovativeness. Urban Stud 39:993–1002
Wood PA (2005) A service-informed approach to regional innovation – or adaptation? Serv Ind J 25:439–445
Wood PA, Bryson JR, Keeble D (1993) Regional patterns of small firm development in the business services: evidence from the United Kingdom. Environ Plan A 25:677–700
Wooldridge JA (1999) Distribution-free estimation of some nonlinear panel data models. J Econ 90:77–97
Wyrwich M (2012) Regional entrepreneurial heritage in a socialist and a post-socialist economy. Econ Geogr 88:423–445

Chapter 3
The Spatial-Institutional Architecture of Innovative Behaviour

Eric Vaz, Teresa de Noronha, and Peter Nijkamp

3.1 Conceptual Framework

3.1.1 The Trajectories of Technological Development

Over the past few decades, social scientists have developed a worldwide interest in the driving forces and socio-economic impacts of innovation and entrepreneurship (see Nijkamp 2009a, b; Stimson et al. 2006). Innovation has turned out to be a critical parameter of human intelligence and of the cognitive ability of human kind. Nowadays, both factors are considered to be the major drivers of socio-economic and technological change, able to stimulate the continuous production of new products or processes (Audretsch et al. 2006). To persuade society to continuously adopt such changes requires a systematic and integrative combination of knowledge assets managed within a framework of institutions, regulations, and some kind of socio-cognitive mechanisms (Hall et al. 2005).

The complexity of the innovation system is, in general, structured under conditions related to governance systems and their respective spatio-temporal industrial organization and their cognitive capacity. This argument recalls for Schumpeter's interpretation of the propensity of innovations to geographically

E. Vaz (✉)
Department of Geography, Ryerson University, 350 Victoria Street, JOR620, M5B2K3 Toronto, ON, Canada
e-mail: evaz@GEOGRAPHY.Ryerson.Ca

T. de Noronha
CIEO – Research Centre for Spatial and Organizational Dynamics, University of Algarve, Campus de Gambelas – Building 9, 8005-139 Faro, Portugal
e-mail: mtvaz@ualg.pt

P. Nijkamp
Department of Spatial Economics, VU University Amsterdam, De Boelelaan 1105, 1081 HV Amsterdam, The Netherlands
e-mail: p.nijkamp@vu.nl

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group and generate clusters, which encourages innovation as a powerful instrument of growth. Against this background, innovation and its constituents have become of crucial interest, and, hence, tracing the complexity of governance systems is one of the key factors to explain the success of efforts to promote innovation. Countless efforts have been made to identify such factors: for example, some researchers have adopted a resource-based view of the firm by accepting the heterogeneous character of firms and emphasizing their strategic behaviour (Knudsen 1995; Noronha Vaz and Cesário 2008).

When knowledge became recognized as a key resource for firms and other economic agents, some authors demonstrated the essential role of linkages between industry and external research organizations for the successful transfer of technological knowledge among firms. This idea was later extended and referred to as the 'Triple Helix concept', a triangular interaction between the research community, governments and industries, which was seen as the solution to successful innovation (Doloreux and Parto 2005).

As linkages between institutions became long lasting and consistently robust, it became possible to address the consequent configuration in *forms of networks and/or industrial clusters*. In fact, a great variety of studies on clustering were influential in describing how and why institutions get together to react to competitive pressures. Westlund and Bolton (2006), for example, described clusters as geographical space with normative isomorphism, "where managers and decision makers follow similar values, cognitive references, perceptions, and experiences, therefore with a propensity to connect and pursue analogous patterns of organizational behaviour".

In such a context, the concept of *Regional Innovation Systems* (RIS) was introduced as "a network of organizations, institutions and individuals, within which the creation, dissemination, and exploitation of new knowledge and innovation occurs" (Cooke et al. 2004). This concept influences the perception of the dynamics of clustering, and means that, for a given national or regional economy, technological and industrial development takes place by following certain trajectories determined by spatial systems traced by groups of linked firms, research organizations, policy institutions, government authorities, and financial actors (Teigland and Schenkel 2006).

3.1.2 Networking, the Strategic Choices of Firms and the Spatial Impacts

Basically, the above-mentioned structures when observed from a global perspective tend to follow long-lasting technology trends that could, among other things, help explain the difficulties in reducing the different growth capacities among countries and regions. In general, the causes for this diverse behaviour and the propensity for disadvantages to have a cyclical nature in many lagging parts of the world have long attracted the attention of many researchers and policy makers (Hall and Wee 1995; Landabaso 1997).

As shown by the Italian School founded by the GREMI group (Camagni 1991, 1995a, b) and, later on, by many other Northern European researchers, such as Asheim and Isaksen (2003), *there is a direct contribution of individual firms or even of industrial clusters to foster regional growth*. This finding has been emphasized even more in the research related to *spillover effects*, developed by, amongst others, Kaiser (2002), and Fischer (2006). But, as yet, many factors remain unsolved:

- There are ambiguous concepts related to the definition of the firms' environment. Either from a geographical or from a geometrical perspective, the market area of each firm and its dominant role vary in function or nature.
- Teigland and Schenkel (2006) argue that the firm's environment should be defined by those agents involved in the historical path-dependent development of skills.
- Other authors propose that the firm's environment is mostly responsible for all those strategic interactions that contribute to productive links within the firm's industrial structure.
- Finally, the firm's environment is highly influenced by the nature of the public institutions involved and their regulations, as they may help or obstruct interactions.

Assuming that the firm's environment is formed, and shaped coherently by the presence of significant linkages, functional clusters may be identified (see Porter 1998). And, assuming that, in spite of much uncertainty, where firms face new future needs for resources and clients, cluster formations are still emerging. In this case, it becomes important to detect whether the strategic decision of firms is internal or external driven: Langlois and Robertson (1995) first developed the idea that many questions related to firm strategy and firm boundaries are correlated. As assessed by Freel (1998), not much is understood about how technologically innovative firms grow, learn, or adapt to transformations taking place in their environments, therefore: (i) Will the strategic choices be solved by firms using market solutions? (ii) And if so, through which decision-making process will this take place?

Frequently, innovative firms accumulate knowledge through learning, as a process to reduce uncertainty, and not necessarily to obtain economies of scale. Therefore, by facilitating better decisions, knowledge acquisition could engage the entrepreneur in strategic learning – an option to absorb economies of scope rather than scale. Thus, the routines of innovative firms will be different from those of their non-innovative competitors.

Empirical studies often underline the role of the firms' environment as the local context within which firms develop their activities (Keeble 1997; Freel 1998) in an interactive mode between the parts and the set (Noronha Vaz 2004). This demonstrates that organizational learning and institutional networking may be combined to boost the performance of innovative firms (Fagerberg 2003).

Occasionally, firms find possible solutions in specific networks for technological learning through external sources, and manage interfaces which help them to combine sources of technical know-how, information, and relations (Stough et al. 2007). In such cases, firms may also be organized in institutional local networks. In the remaining part of our study, we pay attention to the geographical and institutional support systems for innovative firms, with an evidence-based statistical modelling approach to Portugal.

3.2 Measurement of Institutions' Innovative Behaviour at a Regional Scale

3.2.1 Technological Regimes

At the same time that innovation and entrepreneurship were accepted as major factors of growth, the measurement of innovative activities was also receiving much scientific and public attention. However, the measurements related to this systemic concept are still in the process of development. Since the 1990s, statistical surveys have supplied data concerning proxies such as R&D expenditures and the number of patented inventions. Sometimes such proxies were improved by adding up employment in R&D-related activities or other data of a similar kind, but, so far, it cannot be confirmed that there is agreement about an unambiguous direct measure of innovation outputs.

Because the market structure influences innovative activities and the extent to which technological change has an impact on the size distribution of firms, a great part of the research performed is of an empirical nature, and mostly concerns advanced industrial countries. Rarely, have studies addressed rural or lagging areas (Noronha Vaz 2004). This issue dates back to 1991 (see Acs and Audretsch 1991), and invariably indicates that there are considerable ambiguities and inconsistencies in the results of empirical studies directly relating R&D or patents to innovation, particularly in less favoured areas.

Innovation output indicators have often been defined as a proxy for the total number of innovations. Kleinknecht and Bain (1993) proposed several methods for collecting data: postal surveys for self-assessment by managers of their innovations, or literature-based counting of innovations (in trade journals). Both these methods helped to highlight the issues, indicating related ways to work towards general inquiries. Applied in different countries – the first method in Great Britain, Norway, Denmark, Germany and the Netherlands, and the second one in United States, the Netherlands and Ireland – these methods proved to be quite subjective, making a scientific consensus difficult for the general use of the scientific community.

The European Community Innovation Survey (CIS) – implemented by EUROSTAT to collect *firm-level data on inputs to, and outputs of, the innovation* process across a wide range of industries, and across European Member-States and, occasionally, across regions – facilitated progress in comparative analyses of innovativeness across firms, regions, and nations. CIS has its limits, but it does provide evidence of the actual composition of inputs used by the firms to implement technological change. In terms of expenditures committed in the EU to innovative activities, formal R&D in labs accounts for only 41 % of the total, product design costs 22 %, and tooling up and training about 37 %.

Also, at the macro-level, the available data suggest that firms, in particular, or institutions, in general, are job creators and engines of economic growth. However, there is insufficient scientific evidence on the precise role that firms play in the growth mechanisms. Within the context of a learning economy, all enterprises have to adapt their technology to new standards of distribution and to logistic channels, in particular, when operating in an environment of intense competition. There, all categories of enterprises, which may belong to different regional or local innovation systems, are interacting and competing for innovative and market activities, using the same tools and the same knowledge flows (Lester 2006).

The thesis adopted in our study is that regional or local innovation systems result from historical, path-dependent processes, with high degrees of institutional and organizational specificities – *the technological regimes.* Firms, in particular, and institutions, in general, are embedded in a technological regime, and are operating according to the level and type of opportunities for innovations, the accumulation of technological knowledge, and the means of knowledge transmission. The examination of the technological regime of an industry makes it possible to predict, to a certain extent, the kind of enterprises that may innovate, because of the possibilities for protecting innovations, the strength of a dominant design, the nature and the continuity in the learning processes, and the *tacitness* of knowledge and the means for its transmission.

The above theoretical framing outlined above suggests that regional imbalances should be studied by means of obtaining a better understanding of the regional firms' capacity to dynamically innovate. The fact that such capacity may be quantitatively addressed and analysed helps to support the argument even further. Consequently, a key question for further investigation is to detect *firms' innovation patterns*, sort out their structures, and treat them as *facilitators of regional or local growth.*

3.2.2 A Meso-Economic Model to Evaluate the Structures of Innovation

A multilevel model able to improve the analytical tools is required for a better understanding of the complexity expressed by all the determinants of knowledge and innovation outlined above. Figure 3.1 shows the model in which knowledge assets are circulating simultaneously between the micro- and macro-levels of economic activity. The architecture of this model is as follows:

- An exterior cycle represents the global conditions for change, in general, mostly related to the macroeconomic conditions for growth such as GDP, employment, taxes, rates of interest, investment climate, and inflation;

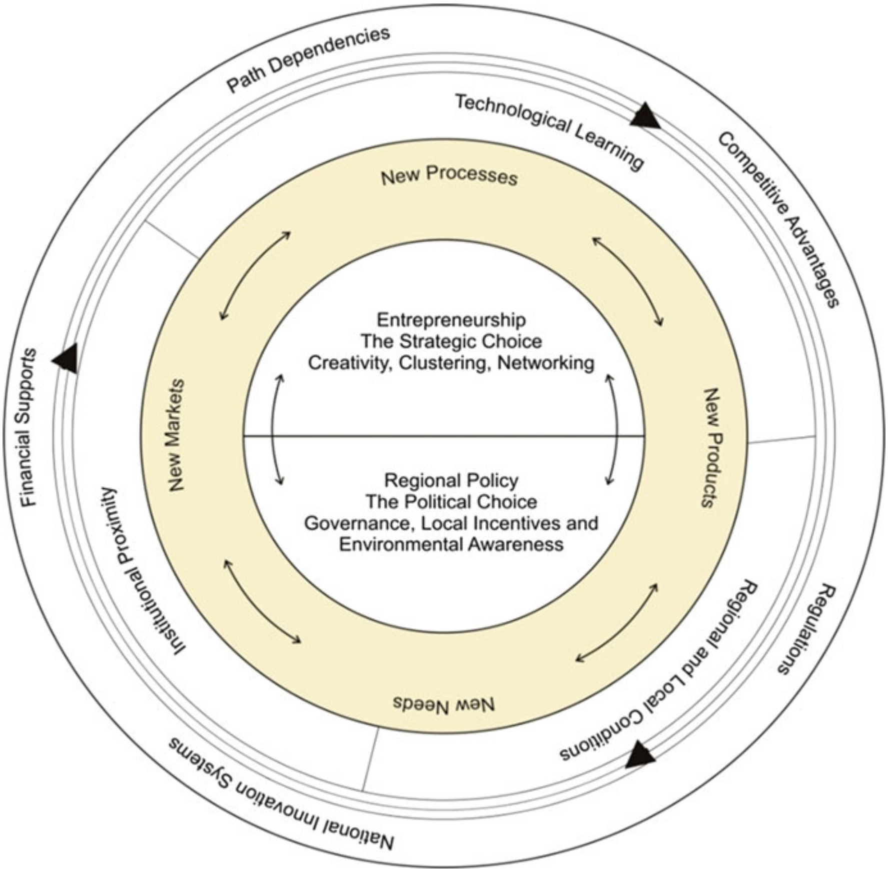

Fig. 3.1 The knowledge circuit (**Source**: Noronha Vaz and Nijkamp (2009))

- The intermediate cycle reproduces the knowledge diffusion taking place at the meso-economic level where institutional relationships occur in the form of: institutional proximity, technological learning, and regional or local conditions:
- There is a permeable boundary between the intermediate cycle and the interior one. Economic effects cross this boundary in the relevant domains associated with organizational management (entrepreneurship, strategic choices, creativity, clustering and networking) and regional policy (political choices, governance, regulation and environmental awareness) which determine an interior cycle which embodies knowledge application that may end up in new products and processes. The core of the cycle illustrates a sharp microeconomic component confined to critical aspects such as market competition, costs, prices, and marketing issues – they are the ultimate facilitators of the success of new products and processes.

In this chapter we concentrate our attention exclusively on the intermediate cycle, the meso-economic level. Our goal is to model the capricious, eventually frenetic, state of relationships occurring among institutions, happening as result of

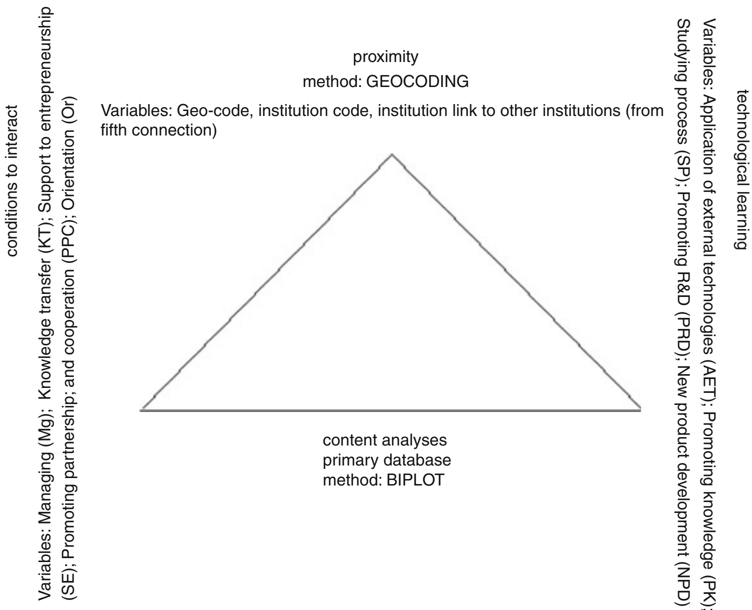

Fig. 3.2 Firms' innovative behaviour model (FIBM)

the three factors: *proximity*, *learning, and cooperating,* in the presence of *regional or local conditions conducive to interaction.*

We assume that a firm's proximity can be mapped out by a GIS application to a statistically significant sample of institutions, if possible by tracing their interaction with other actors which belong, or do not belong to the same sample. Learning and cooperating (measured as technological learning) and external conditions conducive to interaction are variables obtained by means of a direct approach to institutions, either by using questionnaires or by consulting the respective web-sites and with applications of content analyses for the primary data obtained. Figure 3.2 presents a model structure for measuring the firms' innovative behaviour in which spatial, institutional and environmental conditions are combined. This model is called the Firm Innovative Behaviour Model (FIBM).

3.3 Application of the Firms' Innovative Behaviour Model

3.3.1 Database

Our investigation applies the previous model (FIBM) to an extensive set of Portuguese private and public institutions detected by their WebPage contents on innovation: 820 Internet sites were detected and interpreted, eventually resulting in a filtered sample of 623 institutions (which were considered to be able to provide reliable data through their respective websites). These institutions were classified into nine groups, each characterized by ten variables.

The selection of the variables was based on earlier developed research work (for more details see Noronha Vaz and Nijkamp 2009, for the theoretical basis, and Vicente et al. 2010, for the measurement methods). The various constructed variables are assumed to be good proxies of factors favouring innovation, and are identified *as attributes of innovation*. To follow our meso-economic model assumptions, these ten attributes (defined as variables in the model) have been grouped (as in Fig. 3.2) into two classes: (1) Variables for technological learning: Application of external technologies (AET); Promoting knowledge (PK); Studying process (SP); Promoting R&D (PRD); New product development (NPD); (2) Variables for improving conditions conducive to interaction: Managing (Mg); Knowledge transfer (KT); Support to entrepreneurship (SE); Promoting partnership and cooperation (PPC); Orientation (Or).

As grouping factors the following institutions, the *actors of innovation*, have been considered: governmental agencies, associations, technological parks and science centres, R&D organizations, entrepreneurship support entities, technological schools, university interfaces, financial institutes – as well as venture capitalists or high risk investors, and, finally, other institutions.

As pointed out in the theoretical model, a third group of variables was constructed to evaluate spatial proximity. These were formed by geo-coding each innovative institution[1] and its respective links to other institutions with which each institution had maintained cooperation (from first to the fifth connection) of any sort for the period of time considered. All variables were derived by using two different but complementary methodologies: BIPLOT and SPATIAL CONNECTIVITY. The observed time period was the year 2006, so that the analysis has a static-comparative nature.

3.3.2 The Research Methods

3.3.2.1 The BIPLOT Analyses

The information used in our analysis was organized in an I $\times$ J binary data matrix obtained from several innovation attributes, in which the I rows correspond to the above-mentioned 623 institutional units (18 governmental entities, 297 companies, 70 associations, 20 technological parks and centres, 58 R&D organizations, 48 entrepreneurship support entities, 12 technological schools, 80 university interfaces, and 14 other entities) and the J columns correspond to the above-mentioned 10 binary innovation characteristics scored as binary variables, viz. present or absent: (PK), (SP); (Mg); (PRD); (KT); (SE); (NPD); (PPC); (AET); (Or).

[1] Innovative institutions were classified following the previous research in Vicente et al. (2010).

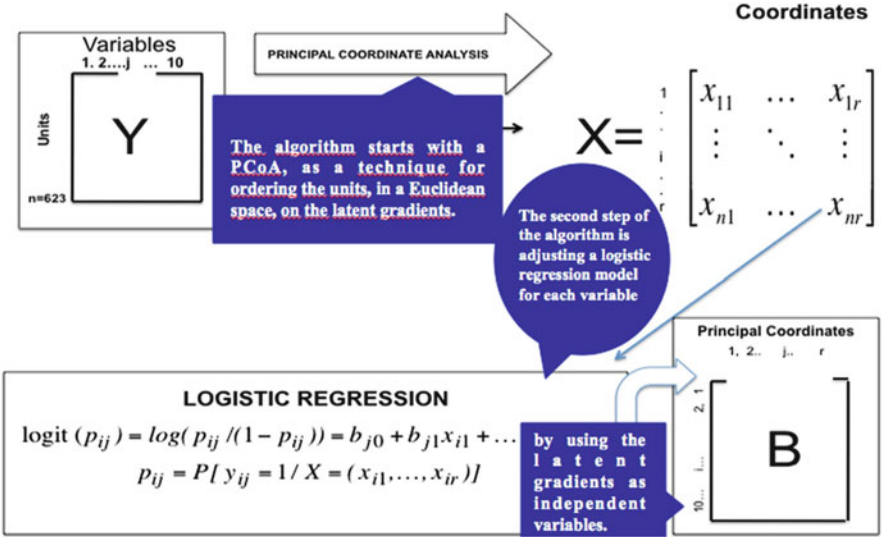

Fig. 3.3 Steps for external logistic biplot (**Source**: Vicente et al. (2010))

The applied statistical algorithm was described in Demey et al. (2008). The procedure to perform the External Logistic Biplot method is based on a Principal Coordinates Analysis, while, next, in a second step of the algorithm, a logistic regression model was used for each variable as illustrated, in Fig. 3.3.

The geometric results represent the principal coordinate scores in a map where the regression coefficients act as vectors indicating the directions that best predict the probability of the presence of each variable.

According to the geometry of the linear Biplot for binary data (see Vicente-Villardón et al. 2006), each variable is represented as a direction vector through the origin. For each variable, the ordination diagram can then be divided into two separate areas predicting presence or absence, while the two areas can be separated by a line that is perpendicular to the characteristic vector in the Biplot, and cuts the vector at the point which predicts a 0.5 probability.

The characteristics associated with the configuration are those that adequately predict the respective presences. Once the coordinates of the points which represent the entities (in our case the institutions) in the plane are obtained by the External Logistic Biplot, we can apply a K-Means analysis to identify the centroids of the resultant clusters. To produce an elegant solution, we may present a Voronoi diagram of the spatial relationships.

The method described above was applied to our data sample, thus eventually indicating the existing force field of the Portuguese innovation system. Figure 3.4a represents a Voronoi diagram of the existing spatial relationships. Four well defined clusters can be detected, each characterized by the presence or the absence of the different sets of variables. Cluster 1 is characterized by the presence of SP, AET, and NPD and the absence of SE; Cluster 2 is characterized by the presence of PK,

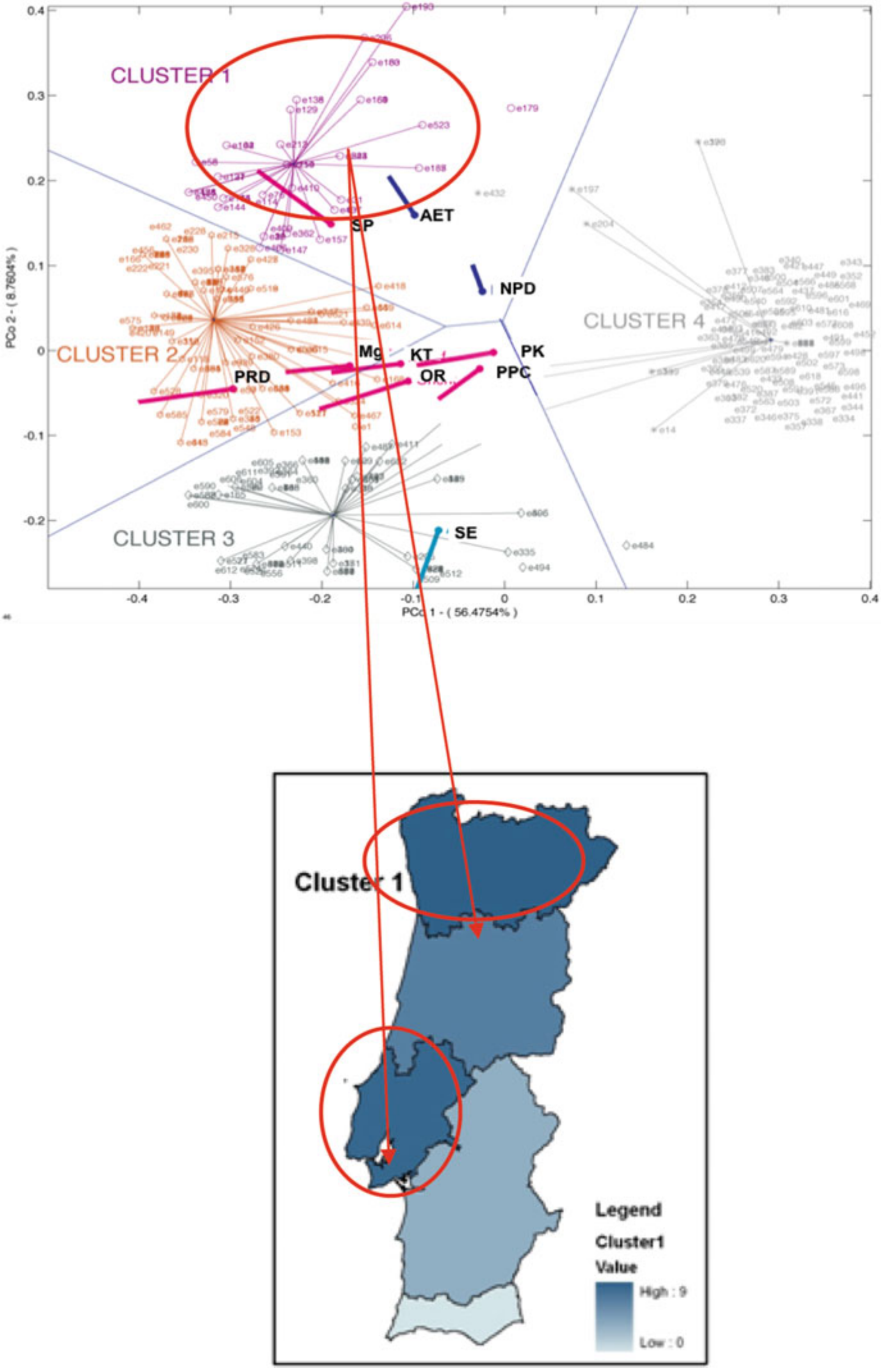

Fig. 3.4 (**a**) Logistic BIPLOT and Voronoi diagram representations of spatial relationships and clusters of innovative institutions in Portugal. (**b**) Regional distribution of Cluster 1 in Portugal

PPC, OR, KT, Mg and PRD, and the absence of SE; Cluster 3 is characterized by the presence of SE, PK, PPC, OR, KT, Mg and PRD and the absence of NPD, AET and SP. Cluster 4 is characterized by the absence of all the indexes of innovation. In terms of the characteristics of the institutions, Cluster 1 has been identified as the cluster which contains the largest number of institutions, and is therefore the most innovative one. Figure 3.4b represents the regional distribution of the institutions of Cluster 1 in Portugal, showing that this cluster is mostly represented in the regions of Lisbon and Norte.

The application of this method can be extended to different observation levels, including the regional or the local level. If the databases provided are sufficiently available at a detailed geographical scale, it is possible to address even the local level. In such a case, the number of observations should be sufficient for the statistical application of the Biplot method. As this is not always the case, in particular in peripheral regions, the density of the entrepreneurial tissue constitutes the first major obstacle to the use of FIBM. Nevertheless, in the next subsection we will consider a more detailed geographical scale by using GIS methods.

3.3.2.2 Spatial Connectivity Results

The use of detailed spatial information has made it possible to understand the relations over space of different types of features (Jankowski 1995). The spatial properties of location of activities and their respective impacts are still far from being completely understood, and have developed into a complex integration of economics, mathematics, and geography. A reason for this is the underlying complexity of the spatial patterns formed (Gustafson 1998), and the connectivity established among the different agents in a complex network of interactions over space, as is illustrated traditionally in studies in ecology (Moilanen and Hanski 2002).

The possibility to merge the configuration of features with networks may be assessed elegantly through generating a network which connects the spatial information concerning features. The connectivity of features in space, allows us to understand and foster the dynamics of collaborations of innovation from a spatial perspective. This was achieved by converting the provided street addresses of the businesses into a point vector in space. The address is categorized into its locational determinants: its street number, street name, and postal code. All this information was then added into ArcGIS 10.1 where the process of spatial connectivity – correspondent to the transformation of the address into a point – was carried out. The geocoded addresses were then exported into Google Earth, to match the consistency of the location with the attribute properties of the surrounding area, and the meta-data related to the geocoded feature were confirmed.

In our empirical case, all the institutions belonging to Cluster 1, which were assumed to be the most innovative ones, were investigated, and their respective links reported up to the fifth connection – considered at any geographical level (local, national, or international). Because several institutions had no reported links,

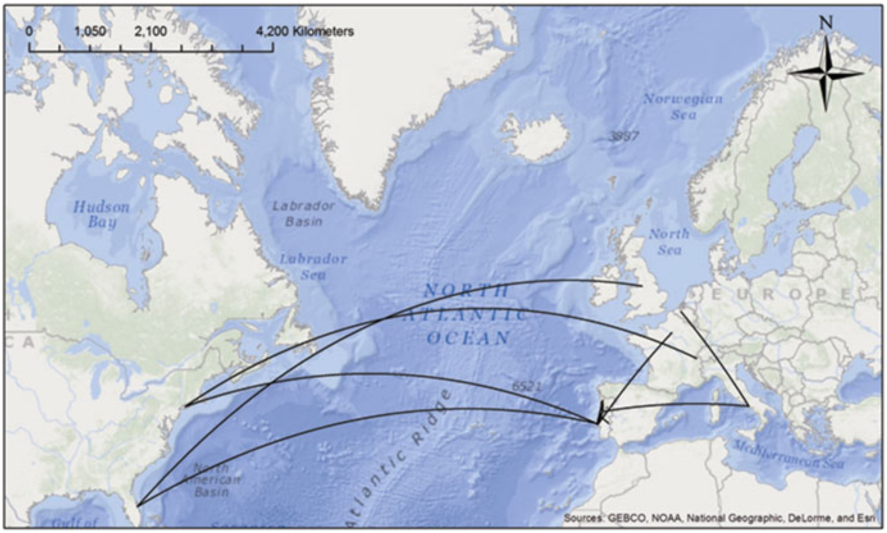

Fig. 3.5 Flow design for international connections

the sample that was used for our mapping procedure was reduced to 37 institutions in a total of 65 point features. The point features were then aggregated into groups corresponding to their partners, defining 15 aggregated groups. These groups of points were then connected by the relevance of the indicated partners, allowing us to establish a spatial understanding of small networks with spatial connectivity. These points were then converted into line segments and projected accordingly on the map.

Figures 3.5, 3.6 and 3.7 define the connections found at different scales: global, national, and local, in relation to the 50 most innovative institutions in Portugal, all included in Cluster 1 and considered to be the most innovative in the country. Only a few relationships are found to exist between the spatial component of countries and business innovators. In fact, most of the relationships, even at national level, are found only north the Tejo valley, with Lisbon and Porto being the main hubs for partnerships.

3.3.2.3 General Findings

By detecting the types of patterns of structures of innovation in Portugal, many advantages and fragilities may be identified and clearly interpreted from a meso-economic perspective. In this context, the above-mentioned FIBM (see Fig. 3.2) approach may be helpful:

- FIBM delivers a combined method able to evaluate the kind of connections underlying the innovation taking place in a certain region or country;

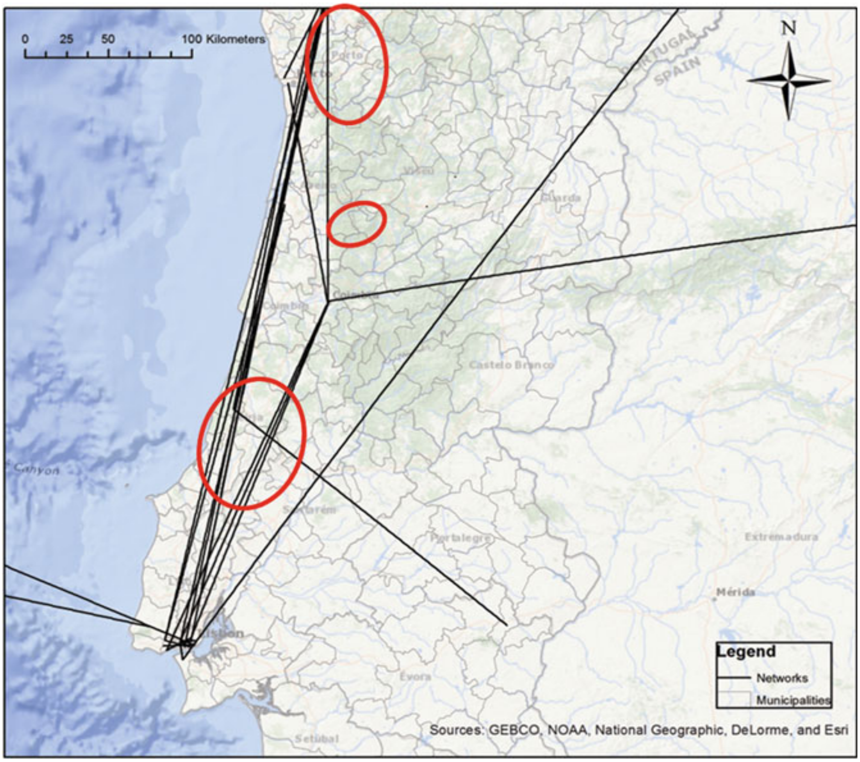

Fig. 3.6 Flow design for internal connections in Portugal

- In our particular case, Portugal, we can confirm an asymmetric flow distribution resulting from the connections from the most innovative institutions, which have based their innovation above all on the study of processes (SP), on the use of external technologies (AET); and on new product development (NPD);
- The asymmetric distribution shows that the most important flows are concentrated in the Lisbon area and Oporto (in the latter, case less intensively) and occasionally extend across Europe or to the USA. When observing the connections at the country level, we can find two hubs and a small focal point in the Centro region. The method allows us to pick up the individual institution responsible for this flow, and search for its innovative prospects.
- Contrary to what was expected, not many connections start at the same point in the Lisbon region. This indicates that different institutions are able to sustain their own innovation paths in a structure that – although in itself is not very complex or elaborated – represents inter-connections at an elaborated level.

Fig. 3.7 Details of connections in the Lisbon area

3.4 Conclusion

This chapter has described a spatial-institutional model for mapping out institutions' innovative behaviour (FIBE) which is able to offer several advantages to both managers and policy makers who wish to assess companies performance.

Managers of companies or other institutions can compare their individual profiles, reproduced in a geometrical location, with that of the system's average by using a simple tool, and then conclude whether or not they should reinforce specific measures to improve their relative positioning – this may be done by looking strategically for a more rigorous use of the missing attributes.

Policy makers and planners may also find the FIBE to a powerful tool. As pointed out, this study confirms the need to implement *tailor-made policies* to encourage innovation at the regional level. This is only possible when it is possible to identify the specific choice of attributes used by the set of companies and other institutions. The innovation patterns that they detect may suggest those specific measures which are required to act directly on each described critical success factor, contributing to a new concept of intervention – the *regional cluster-architecture*, in order to help focus policies for regional development.

Furthermore, the examination of connectivity flows suggests that the emergence of innovation is also a result of the flow intensity, which thus identifies the innovation processes as being spatially determined. Therefore, general policies to promote regional innovation will be inefficient able to be entirely efficient if the spatial flows structure is not considered. The resulting paths may create some path dependency; and, in that case, the efficiency of promoting innovation policies in such environments may tend to increase.

References

Acs ZJ, Audretsch DB (1991) Innovation and technological change. An international comparison. The University of Michigan Press, Michigan

Asheim BT, Isaksen A (2003) SMEs and the regional dimension of innovation. In: Ascheim BT (ed) Regional innovation policy for small-medium enterprises. Edward Elgar, Cheltenham, pp 21–46

Audretsch DB, Keilbach MC, Lehmann EE (2006) Entrepreneurship and economic growth. Oxford University Press, Oxford

Camagni R (1991) Introduction: from the local milieu to innovation through corporation networks. In: Camagni R (ed) Innovation networks: spatial perspectives. Belhaven Press, London/New York, pp 1–9

Camagni R (1995a) Espace et temps dans le concept de milieu innovateur. In: Ralllet A, Torre A (eds) Économie Industrielle et Économie Spatiale. Economica, Paris, pp 193–210

Camagni R (1995b) Global network and local milieu: towards a theory of economic space. In: Conti S, Malecki E, Oinas P (eds) The industrial enterprise and its environment: spatial perspectives. Ashgate, Avebury, pp 195–213

Cooke P, Braczyk HI, Heidenreich M (eds) (2004) Regional innovation systems: the role of governances in a globalized world, 2nd edn. Routledge, London

Demey JR, Vicente-Villardón JL, Galindo MP, Zambrano AY (2008) Identifying molecular markers associated with classifications of genotypes by External Logistic Biplot. Bioinformatics 24:28–32

Doloreux D, Parto S (2005) Regional innovation systems: current discourse and unresolved issues. Technol Soc 27:133–153

Fagerberg J (2003) Schumpeter and the revival of evolutionary economics: an appraisal of the literature. J Evolut Econ 13:125–159

Fischer MM (2006) Innovation, networks and knowledge spillovers. Springer, Berlin

Freel M (1998) Evolution, innovation and learning: evidence from case studies. Entrepr Reg Dev 10(2):137–149

Gustafson E (1998) Quantifying landscape spatial pattern: what is the state of the art? Ecosystems 1(2):143–156

Hall R, Wee M (1995) The regions in a enlarged Europe. In: Hardy S, Hart M, Albrechts L, Katos A (eds) An enlarged Europe. Regions in competition? vol 6, Regional policy and development. Jessica Kingsley Publishers/Regional Studies Association, London, pp 8–21

Hall P, Crouch C, Streeck W, Boyer R, Amable B, Jackson G (2005) Dialogue on institutional complementarity and political economy. Socio-Econ Rev 3:359–382

Jankowski P (1995) Integrating geographical information systems and multiple criteria decision-making methods. Int J Geogr Inf Syst 9(3):251–273

Kaiser U (2002) Measuring knowledge spillovers in manufacturing and services: an empirical assessment of alternative approaches. Res Policy 31(1):125–144

Keeble D (1997) Small firms, innovation and regional development in Britain in the 1990s. Reg Stud 31(3):281–293

Kleinknecht A, Bain D (1993) New concepts in innovation output measurements. St Martin's Press, New York

Knudsen C (1995) Theories of the firm, strategic management and leadership. In: Montgomery C (ed) Resource-based and evolutionary theories of the firm. Kluwer, Boston, pp 179–217
Landabaso M (1997) The promotion of innovation in regional policy: proposals for a regional innovation strategy. Entrepr Reg Dev 9(1):1–24
Langlois RN, Robertson PL (1995) Firms, markets and economic change. Routledge, London/ New York
Lester R (2006) Prospects for local innovation systems. Paper presented at a seminar held in September 2006 at the Department of Economics, National University of Ireland, Galway
Moilanen A, Hanski I (2002) On the use of connectivity measures in spatial ecology. Oikos 95 (1):147–151
Nijkamp P (2009a) E pluribus unum. Reg Direct 2(2):56–65
Nijkamp P (2009b) Regional development as self-organized converging growth. In: Kochendorfer G, Pleskovic B (eds) Spatial disparities and development policy. World Bank, Washington, DC, pp 205–282
Noronha Vaz T (2004) The environmental context for small firms in the EU. In: Noronha Vaz T, Morgan E, Wigier M (eds) Innovation in small firms and dynamics of local development. Scholar Publishing House, Warsaw, pp 13–31
Noronha Vaz T, Cesário M (2008) Driving forces for innovation: are they measurable? Int J Foresight Innov Policy 4(1–2):30–50
Noronha Vaz T, Nijkamp P (2009) Knowledge and innovation: the strings between global and local dimensions of sustainable growth. Entrepr Reg Dev 21(4):441–457
Porter ME (1998) Clusters and the new economics of competition. Harv Bus Rev 76:77–90
Stimson R, Stough R, Roberts BH (2006) Regional economic development. Springer, Berlin
Stough R, Nijkamp P, Vaz MTN (eds) (2007) Local Knowledge and Innovation Policy in Government and Policy. Special Issue of Environ Plan C 25(5):633–637
Teigland R, Schenkel A (2006) Exploring the role of communities of practice in regional innovation systems. In: Coakes E, Clarke S (eds) The encyclopaedia of communities of practice. In information and knowledge management. Idea Group, Hersley
Vicente P, Noronha Vaz T, Nijkamp P (2010) Institutional capacity to dynamically innovate: an application to the Portuguese case. Technol Forecast Soc Change 78(1):3–12
Vicente-Villardón JL, Galindo-Villardon MP, Blazquez-Zaballos A (2006) Logistic biplots. In: Greenacre M, Blasius J (eds) Multiple correspondence analysis and related methods. Chapman Hall, Boca Raton, pp 503–521
Westlund H, Bolton R (2006) Local social capital and entrepreneurship. Small Bus Econ 21 (2):77–113

Websites

Community Innovation Survey (CIS) http://epp.eurostat.ec.europa.eu/cache/ITY_OFFPUB/KS-EM-08-001/EN/KS-EM-08-001-EN.PDF

Chapter 4
The Determinants of FDI Choices: The Importance of Investment Climate and Clustering

Megha Mukim

4.1 Introduction

Recent work on factors that determine the choices made by foreign investors within and across countries has been growing rapidly – see Mukim and Nunnenkamp (2012) for a comprehensive review. However, the cross-country literature on how the investment climate affects decisions made by foreign investors using robust methodological approaches is lacking. Indicators of foreign investment regulation that has been standardised across countries could lend itself for different types of empirical analysis. This paper will use data made available by the Investing Across Borders database of the World Bank Group, to study how the investment climate across sectors and countries affects the choice of new investment projects across different countries.

The study will also address that strand of the economic geography literature that predicts that similar firms are drawn to the same locations. Following other papers, similarity will be defined in terms of country of origin and of sector, the assumption being that clusters of similar firms within a country may matter for regional production networks, and may benefit from knowledge or other spillovers.

The main motivation underlying this study is that if policy makers are interested in attracting FDI to particular countries or regions, they should have a sound understanding of the factors that affect investors' location decisions. And while

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M. Mukim (✉)
World Bank, 1818 H Street NW, 20433 Washington, DC, USA
e-mail: mmukim@worldbank.org

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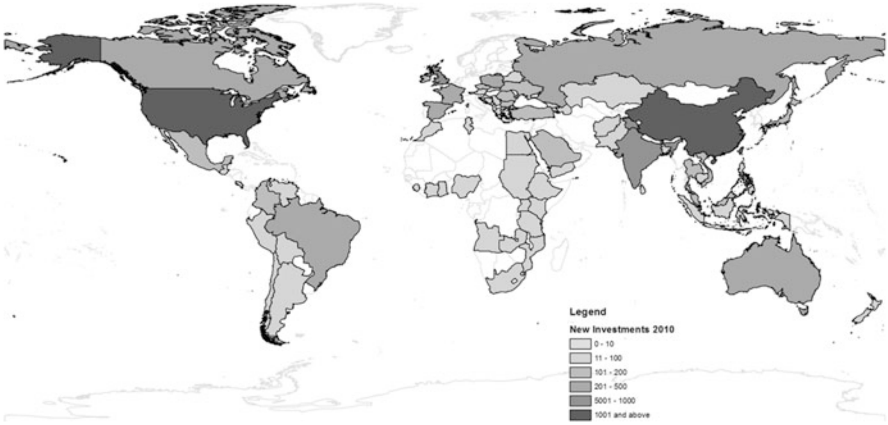

Fig. 4.1 Distribution of FDI (Source: fDi Markets. Note: There is no information available for the countries shown as semi-transparent)

there is much research to show how attributes of a location matter at smaller spatial scales, such as states or metropolitan regions, there is little research to provide an understanding of these affects at the level of national decision-making. Indeed, if one were mainly concerned with being a magnet for large-scale and long-term foreign direct investments, then cross-country analysis might provide useful insights.

The relevance of regional attributes in location choice is suggested by the regional distribution of new investments made in 2010. As depicted by Fig. 4.1, there is much evidence of new foreign investments clustering in particular countries. New investments tended to be concentrated in particular countries such as the United States, China, India, the United Kingdom, Russia, Spain, France and Australia. In fact 50 % of all new investments seem to be concentrated in just 10 countries, and 40 countries account for 90 %. Although data is not available for all countries, this does seem to suggest that foreign investors seem to consistently favour particular countries over others. The bulk of the following analysis will be concerned with estimating what degree of this concentration is driven by existing location decisions made by previous investors, and what might be driven by factors relating to the business and investment climate within a country and/or sector. The study will also control for GDP per capita rates of growth averaged over the last 5 years, and wherever possible bilateral distances.

While the map provides a birds' eye view of where investment locates, Fig. 4.2 describes how these investments are distributed across sectors and regions. Clearly, manufacturing accounts for the largest proportion of most foreign direct investments, and this dominance seems fairly stable across different regions, with the slight exception of APEC. Other important sectors are telecommunications, banking and mining industries.

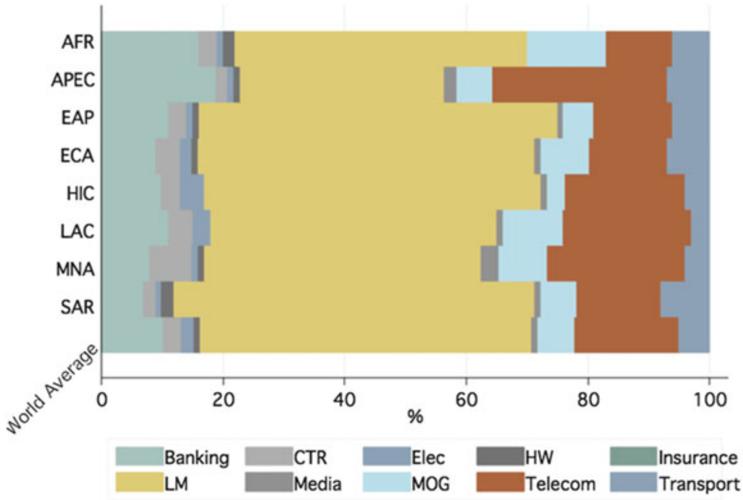

Fig. 4.2 Composition of investments by sector and region (Notes: Regions include: *AFR* sub-saharan africa, *APEC* asia pacific economic co-operation, *EAP* east asia and pacific, *ECA* eastern europe and central asia, *HIC* high-income OECD, *LAC* latin america and caribbean, *MNA* middle east and north africa, *SAR* south asia. Sectors include: *CTR* construction tourism and retail, *HW* health and waste, *LM* light manufacturing, *MOG* mining oil and gas)

In summary, there is much evidence to suggest that foreign investments tend to concentrate in particular countries and to some extent across particular sectors. Given that certain countries are able to attract a disproportionate share of investment activity, it will be instructive to know what characteristics in particular might be driving these trends. Thus, this paper will model the location decisions of new foreign investments for 87 countries, and will identify to what extent the investment climate within these countries might be driving these decisions.

The remainder of this paper is organised as follows: Sect. 4.2 provides a theoretical explanation of the factors influencing the location of investment and presents evidence of how these theories have been tested empirically in the literature. Section 4.3 lays out the estimation framework and discusses the main sources of data. Section 4.4 presents and discusses the results of the model. Section 4.5 addresses endogeneity issues and carries out robustness tests. Section 4.6 concludes and discusses the implications of the findings.

4.2 Theoretical Background and Related Literature

Models of location choice by foreign investors have addressed various factors that may help explain the concentration of FDI across and within host countries. Typically, the theoretical starting point is that foreign firms decide on a particular location based on expected profitability. The Helpman et al. (2004) model would predict that the most productive firms would engage in FDI, while others would choose to supply the domestic market or export.[1] Indeed, to serve foreign markets, firms first choose between exporting and investing – see Brainard (1997) and Lankhuizen et al. (2011) for a discussion. This paper will focus its attention on those firms which have chosen to invest abroad in place of exporting. Ultimately, location choices depend on how the characteristics of one particular region (and its geographical environment) affect firms' profits relative to the characteristics of other regions. The literature on FDI distinguishes between patterns of vertical and horizontal internationalization. The vertical pattern is explained by the factor proportion approach, developed by Helpman (1984) and Helpman and Krugman (1985). Markusen (1984, 2002) and Markusen and Venables (1998) developed the theories of horizontal patterns. Markusen (1997, 2002) unified these two approaches into the knowledge-capital model. Some of the important factors shaping these choices include expected demand for a firm's products, the supply of required inputs, factor costs, and the economic policy environment. In addition, previous location choices by peers and competitors figure prominently on the list of FDI determinants and have received particular attention in the recent empirical literature.

Well-functioning infrastructure and the general business environment can be expected to be important regional pull factors of FDI. Even as early as the second half of the 1990s, UNCTAD had argued that foreign investors were increasingly pursuing so-called complex integration strategies. Accordingly, host countries would have to offer "*an adequate combination of the principal locational determinants .... important for global corporate competitiveness*" (UNCTAD 1998, p. 112), including sufficiently skilled labour, adequate infrastructure facilities and specialised support services. Indeed, as described by Blonigen (2005), the quality of institutions is one of the more important determinants of the level of FDI received by a country or region and this could be the case for a variety of reasons. Investment might be less likely in countries where there is inadequate protection of investors' assets, or if endemic corruption increases the cost of doing business or impinges upon the legal rights of investors. The absence of well functioning institutions might also be reflected in the general business environment within a country in the form of poor quality infrastructure or cumbersome and time-consuming procedures for doing business.

Cross-country comparisons of FDI location choices are rare, and usually focus on agglomeration forces. One of the first papers that studies the issue is by Wheeler and Mody (1992) who find that a host country's risk factor, which they measure as a composite index of corruption, overall living environment etc, has no effect on inward FDI. In another paper, Hines (1995) studies the correlation between local corruption in host countries and FDI flows and finds a similar result. He concludes that the latter seem to be unaffected by the former, and that the only flows that were

[1] Owing to lack of data on firm-level inputs and outputs, or measures of productivity, this paper will be unable to test the predictions of their model.

affected were those subject to the US Foreign Corrupt Practices Act. On the other hand, Wei (2000) studies the effect of corruption on countries' ability to attract FDI and concludes that deterioration in the investment climate within a country has the same effect of discouraging foreign investment as a large increase in the tax rate. Mataloni (2009) finds that US enterprises investing in Europe evaluate locational attributes such as industrial agglomeration and labour market conditions at the national and then sequentially, at the sub-national level. Papers (Resmini 2000; Carstensen and Toubal 2004) studying investments across transition countries find that relatively low labour and factor costs are important incentives. Nunnenkamp and Mukim (2012) find that peer effects, i.e. same-country, FDI exert a significant pull on the location decisions of new investments in India.

Since the descriptive analysis clearly seems to indicate that FDI is drawn to particular countries over others, I am also interested in assessing the self-reinforcing effects of FDI on current choices. The effects of previous presence of foreign investors in US states on subsequent location choices have received particular attention. Bobonis and Shatz (2007) find that an additional 1 % of FDI stock from a particular source country in a particular US state boosts the value of subsequent FDI from that source country in that state by 0.11–0.15 %. Head et al. (1995) find that Japanese investors in the US were attracted to locations where initial investments were within the same industry groups. Blonigen et al. (2005) also study the location choices of Japanese FDI in manufacturing industries of US states and find that the likelihood of a state being chosen by a subsequent investor in a particular industry increases depending on previous horizontal and vertical Japanese investments. Head et al. (1999) observe that some rather weakly industrialised US states (e.g., Georgia, Kentucky and Tennessee) attracted substantial Japanese FDI, which eventually rendered these states more attractive to subsequent Japanese FDI than industrial centres such as Massachusetts. Their paper also argues that the separation of self-reinforcing FDI effects involving investors based in the same home country from those involving investors based in other countries of origin is particularly useful in identifying such developments.

On the other hand, Guimaraes et al. (2000) find the self-reinforcing effects of previous location choices by foreign investors to be rather weak in Portugal. Interestingly, however, compared to the aforementioned studies on FDI at the level of US states, Guimaraes et al. analyse agglomeration economies at a much finer regional level, namely the 275 (fairly small) Portuguese conselhos. As pointed out by Coughlin and Segev (2000) in the Chinese context previous FDI could also drive away subsequent FDI from economic centres. This might happen if FDI contributed considerably to rising costs of production in a certain location, making the cost situation in neighbouring regions more desirable for followers.

In summary, there is considerable ambiguity concerning the role of institutional characteristics of specific locations as well as previous location choices on new FDI flows. At the same time, empirical evidence remains inconclusive and is largely restricted to a few host countries, notably the United States and China. Additionally, estimating the magnitude of the effect of institutions on FDI can be difficult in the absence of comparable cross-country data. Using new data provided by the

Investing Across Borders database, this study will attempt to fill a yawning gap in the literature by testing the effect of factors that directly influence the investment climate within a country, after separately controlling for the effect of previous investment and rate of growth of market size. The next section will describe the estimating equations, specify the variables and describe the different sources of data.

4.3 Estimation Framework

4.3.1 Econometric Model

A popular model of location choices are conditional logits which assume that firms evaluate alternative locations at each time period and would consider relocation if profitability in another place exceeded that at its current location. In other words, it is assumed that a given investor chooses the country yielding the highest profit. The use of a discrete choice framework to model location behaviour stretches back to the 1970s, when Carlton (1979) adapted and applied McFadden's (1974) Random Utility Maximisation Framework to firm location decisions.

Within such a discrete choice framework, a general profit function is used to explain how a location is chosen. Following McFadden the model assumes a set $J = (1, 2, ...j, ...n)$ of possible locations (countries) assuming that location j offers profitability level π_{ijk} to an investor i in industry k. The resulting profitability equation yielded by country j to an investor i in industry k is:

$$\pi_{ijk} = \beta Z_{ijk} + \varepsilon_{ijk} \tag{4.1}$$

where β is the vector of unknown coefficients to be estimated and ε_{ijk} is a random term. Thus, the profit equation is composed of a deterministic and a stochastic component.

In practice, however, the implementation of the conditional logit model in the face of a large set of spatial alternatives can often be cumbersome.[2] The conditional logit model is also characterised by the assumption of the Independence of Irrelevant Alternatives (IIA). Consequently, the ratio of the logit probabilities for any two alternatives does not depend on any alternatives other than the two considered.[3] This assumption would be violated if some countries were closer substitutes for one another than others.

[2] Guimaraes et al. (2003) provide an overview of the problems and how different researchers have attempted to deal with them in the past.

[3] More formally, this implies that the ε_{ijk}s are independent across individual investors and choices; all locations would be symmetric substitutes after controlling for observables.

Count models have gained popularity as the number of alternative locations increased, since what these lead to computational burdens in conditional logit models but in count models these are an advantage owing to the availability of more numerous observations. Unlike an ordinary least squares (OLS) specification, a count specification would have the added benefit of allowing for the possibility of zero counts. However, count models were at the time not understood to be as theoretically well founded as the conditional logit model, which is based on the RUM framework. This was until Guimaraes et al. (2003, 2004) showed that count models can be specified in a way that is theoretically and empirically consistent with conditional logit models and thereby the RUM framework.

Guimaraes et al. 2003 demonstrate how to control for the potential IIA violation by making use of an equivalence relation between the conditional logit and Poisson regression likelihood functions. In a separate paper, Guimaraes et al. (2004) provide an empirical demonstration. In this model the alternative constant is a fixed-effect in a Poisson regression model, and coefficients of the model can be given an economic interpretation compatible with the Random Utility Maximisation framework.

Information on actual individual investment choices is grouped into vectors of counts without any loss of information. This occurs since there are groups of investors faced with the same choice set and the same choice characteristics. For instance, consider the problem of identification of the relevant regional factors that affect investor location. Typically, researchers view these individual location decisions as profit (utility) maximising actions. Investors from diverse sectors evaluate the characteristics of different regions and choose to locate in the region that maximises potential profits. In this case, it is common to assume that all investors face the same choice set, and the relevant characteristics of the regional choices are identical for investors belonging to the same industry. The available information consists of regional counts of investments by industry and variables that reflect the characteristics of the regions (i.e. countries). Despite the fact that the data consist of individual level choices, the true variation of the data is at the group level. Thus, data for the dependent variable may be summarised by vectors of counts.

This paper will estimate both types of models, counts and conditional logits. Whilst count models are able to control for the IIA assumption and have the additional advantage of being computationally simple to run, conditional logit models make it possible to drill down to the characteristics of each investment choice. In our case, this will be particularly useful in identifying the effect of choices made by investors coming from the same source countries or based in similar sectors, and in accounting for source-destination country distances. The next section will describe the different sources of data, and provide an overview of the variables of interest to be used in the analysis.

4.3.2 Sources of Data and Specification of Variables

The main source of data for the dependent variable is the fDi Markets database, which is maintained and run by the Financial Times. The systematic and daily screening of news, media, government and industry sources provides data on new foreign investment projects. Projects need to meet the following criteria to be included in the database: (1) be more than 50 % foreign ownership, (2) be greenfield, (3) create jobs and (4) be initiated by a corporate entity. The data collection process underestimates new investments made by individuals and entrepreneurs, especially in sectors such as textiles and tourism. Indeed, according to the database, the mean value of a new foreign project in 2010 is US$ 54 million. Also, the coverage of investments made in developed countries is better than that in most developing countries. Projects are classified as those that are new, expanding and co-locating. In this analysis, I include only new projects since I am mainly interested in accessing the location decisions made by new investors – expansion and co-location do not involve genuine location choices since their choice of country or region is explained by the presence of an existing project. After cleaning the data, the total number of new foreign investments made worldwide in 2010 was 9,189.[4]

Data from the Investing Across Borders (IAB) database maintained by the World Bank Group is the main source of the predictor variables. Data from the IAB is used primarily to construct cross-country comparative measures of investment climate, wherein the vector of variables includes 'Investing across sectors' that varies by country and sector, and 'starting a foreign business', 'accessing industrial land' and 'arbitrating commercial disputes' that vary by country.

The dependent variable used in the reduced form specification of the conditional logit model is a dummy variable that equals one for each investment choice and zero otherwise. The dummy varies by sector, source country and destination country. The dependent variable used in the count models is the count of new investments. The count variable varies by sector and country. Since the analysis is based at a point in time, these variables are time-invariant.

The explanatory variables can be classified as falling into three main categories – those that capture the effect of clustering of existing FDI within countries, those that capture the effect of the business environment and the investment climate, and other country-specific controls. Table 4.1 summarises the variables used in the analysis and lists the data sources used. A brief description of the variables follows.

The count of existing investments is taken from the fDi Markets database, and refers to the total stock of investments made between 2003 and 2009. These investments vary by source country, sector and destination country. Since data is unavailable for year before 2003, this stock of FDI will, in all probability, grossly underestimate total stocks. However, for the purposes of this analysis, wherein the existing stock of investments within a country will help to control for other

[4] The database also includes project investments made across states in the US – these are also excluded from the analysis.

Table 4.1 Predictor variables

	Variable	Indicator	Expected sign	Source
Agglomeration	Count of existing projects	Strength of FDI clustering	+	fDI markets
Investing across sectors	Greenfield	Percentage of foreign ownership of equity permitted	+	IAB
Starting a foreign business	Start-up time	Days involved in foreign subsidiary establishment	–	IAB
	Start-up number	Procedures involved in foreign subsidiary establishment	–	IAB
	Start-up ease	Index of ease of establishment	+	IAB
Accessing industrial land	Land lease	Index of strength of lease rights	+	IAB
	Land ownership	Index of strength of ownership rights	+	IAB
	Land info access	Index of access to land information	+	IAB
	Land info availability	Index of availability of land information	+	IAB
	Land private time	Days involved in leasing industrial land from a private owner	–	IAB
	Land public time	Days involved in leasing industrial land from a public owner	–	IAB
Arbitrating commercial disputes	Arbitration laws	Index of strength of laws	+	IAB
	Arbitration process	Index of ease of process	+	IAB
	Arbitration judicial	Index of extent of judicial assistance	+	IAB
Country controls	GDP	Gross Domestic Product	+	WDI
	Population	Population	+	WDI
	Education	Average years of secondary schooling	+	WDI
	Wages	Mean manufacturing wages (monthly)	–	UNECE
	Distance	Country-pair distances	–	CEPII

Note: *IAB* investing across borders, *WDI* world development indicators, *UNECE* united nations economic commission for europe, *CEPII* centre d'etudes prospectives et d'informations internationales

unobservables at the level of the country, stocks over the most recent 6-year period would also suffice.

Greenfield measures the overt statutory restrictions on foreign ownership of equity in new investment projects. The value of the index ranges between 0 and 100; the latter indicating that full foreign ownership is permitted. By definition, this variable varies by country and by sector.

The next set of explanatory variables under the category of 'Starting a Foreign Business' quantifies the procedural burdens that foreign companies face when entering a new market. The subset of indicators serves as proxies for (1) Start-up

Time i.e. the time in days for establishing a subsidiary, (2) Start-up number i.e. the total number of procedural steps involved in established a wholly foreign-owned subsidiary, and (3) Start-up ease i.e. an index (0–100) for the ease of navigating the regulatory regime.

'Accessing Industrial Land' quantifies multiple aspects of land administration regimes that are important to foreign companies seeking to acquire land for their industrial investment projects. The main subset of indicators is as follows (1) Land Lease i.e. an index that measures the strength of leasing rights, which compares whether foreign and domestic companies are treated differently and whether land can be subleased, subdivided, mortgaged, or used as collateral, (2) Land Ownership i.e. an index that measures the strength of ownership rights based on the security of legal rights offered to investors, (3) Land Information Access i.e. an index that measures the ease of access to land-related information through the country's land administration systems, (4) Land Information Availability i.e. an index that measures the availability of key information provided through land administration institutions, (5) Land Private Time i.e. the number of days needed to lease industrial land from a private holder, and (6) Land Public Time i.e. the number of days needed to lease land designated for industrial use from the government.

The last category of indicators is of 'Arbitrating Commercial Disputes', which analyses different aspects of domestic and international arbitration regimes in each country that are applicable to local and foreign companies. The subset of indicators is as follows (1) Arbitration Laws i.e. an index that measures the strength of laws and regulations that regulate domestic and international arbitrations as well as the country's adherence to specific international conventions, (2) Arbitration Process i.e. an index that measures the ease with which parties can design arbitration proceedings in their chosen manner and conduct fair and predictable arbitrations, (3) Arbitration Judicial i.e. an index that measures the extent of judicial assistance to the arbitration proceedings before, during and after the proceedings.

And finally, I also include the average rate of growth of GDP per capita between 2005 and 2009 as an indicator of the size and attractiveness of the market. Data is taken from the World Development Indicators Database of the World Bank. I also include country-pair distances, and expect that the distance between any pair of countries should negatively affect the likelihood of new investments. The distance matrix data is taken from the CEPII.[5] Table 4.2 provides some descriptive statistics for the dependent and the explanatory variables used in the analysis.

The variables taken from the IAB database are also highly correlated – see Table 4.3, suggesting that the dataset is noisy. I will use principle component analysis to reduce the number of variables while still accounting for most of the variation in the explanatory variables. This methodology also has the advantage that the principle components extracted from the variables are uncorrelated with one another.

[5] The bilateral distance data is described and made available by the CEPII on its website: http://www.cepii.fr/anglaisgraph/bdd/distances.htm

Table 4.2 Descriptive statistics

Variable	#	Mean	Std. dev.	Min	Max
Count of new projects	911	10.78	36.29	0	620
Count of existing projects	743	89.61	292.77	1	5,228
Value of new projects	9,189	54 m	295 m	0	16b
Greenfield	812	91.21	19.77	0	100
Start-up time (days)	86	41.12	44.96	2	263
Start-up number (procedures)	86	9.93	4.23	2	21
Start-up ease	86	64.95	14.55	21.1	92.1
Land lease	85	82.07	10.68	44	100
Land ownership	67	92.14	13.85	50	100
Land info access	85	41.53	16.31	0	95
Land info availability	85	71.87	20.73	0	100
Land private time	83	61.46	41.74	7	218
Land public time	82	140.74	75.80	7	355
Arbitration laws	86	86.30	11.15	44.9	99.9
Arbitration process	86	71.86	13.96	0	88.5
Arbitration judicial	86	59.22	21.27	0	98.8
GDP	86	5.53e + 11	1.74e + 12	8.43e + 8	1.44e + 13
Population	86	6.64e + 7	1.89e + 8	622,344	1.32e + 9
Education (years of schooling)	85	6.37	0.99	4	9
Wages (per month US$)	27	1,532	1,563	198	5,269

Note: # refers to the number of countries for which data is available. It refers to the number of sectors and countries for ‘Greenfield’ and the counts of new and existing projects. It refers to the number of individual observations, by country, sector and source country for value of new projects

I carry out the analysis by each category and construct the components provided in Table 4.4. The Eigenvalues refer to the amount of variation that is explained by the principle component – the proportion of the total variation in the data explained is provided in italic parenthesis. The component loadings (or scores) describe which variables contribute to which components. For instance, one could interpret ‘Start-Up’ as being highly positively correlated with start-up time and start-up procedures, and negatively related to the ease of start-up.

The vector ‘Startup’ seems to maximise the variance along the measure of the days and procedures taken to start a business, ‘Land1’ maximises the variance along the measure of the ease, access and availability of land, ‘Land2’ is a rough measure of the time taken to lease private and public land, and finally, ‘Arb’ is a measure of the strength of the judicial system.

4.4 Results and Discussion

4.4.1 Count Models

The modelling choices used in the analysis are based on the characteristics of the data. I illustrate this by using count data for the 2010 cross-section. One of the key

Table 4.3 Pair-wise correlations

	Green	Start1	Start2	Start3	Land1	Land2	Land3	Land4	Land5	Land6	Arb1	Arb2	Arb3
Green	1												
Start1	−0.14*	1											
Start2	−0.11*	0.51*	1										
Start3	0.12*	−0.45*	−0.31*	1									
Land1	0.006	−0.14*	−0.23*	0.33*	1								
Land2	0.18*	−0.07	0.12*	0.55*	0.26*	1							
Land3	0.13*	−0.14*	−0.12*	0.40*	0.27*	0.25*	1						
Land4	−0.02	−0.15*	−0.02	0.40*	0.40*	0.38*	0.32*	1					
Land5	0.04	0.06	−0.07*	−0.10*	−0.31*	0.06	−0.26*	−0.26*	1				
Land6	−0.02	0.13*	0.05	−0.10*	−0.14*	−0.05	−0.27*	−0.13*	0.56*	1			
Arb1	0.01	−0.17*	−0.09*	0.26*	0.39*	0.19*	0.26*	0.42*	−0.15*	−0.14*	1		
Arb2	−0.001	−0.22*	−0.10*	0.23*	0.26*	0.14*	0.19*	0.38*	−0.16*	−0.15*	0.35*	1	
Arb3	0.08*	−0.24*	−0.30*	0.41*	0.44*	0.22*	0.27*	0.41*	−0.19*	−0.08*	0.32*	0.44*	1

Notes: *Green* greenfield, *Start1* start-up time, *Start2* start-up number, *Start3* start-up ease, *Land1* land lease, *Land2* land ownership, *Land3* land information access, *Land4* land information availability, *Land5* land private time, *Land6* land public time, *Arb1* arbitration laws, *Arb2* arbitration process, *Arb3* arbitration judicial

Table 4.4 Principal components

Component	Eigenvalue	Variable	Component loading
Start-up	1.8609	Start-up time (days)	0.6240
	(62 %)	Start-up number (procedures)	0.5683
		Start-up ease	−0.5364
Land1	2.0107	Land lease	0.4130
	(33 %)	Land ownership	0.2749
		Land info access	0.4926
		Land info availability	0.3178
		Land private time	−0.4461
		Land public time	−0.4597
Land2	1.4602	Land lease	0.3836
	(24 %)	Land ownership	0.4633
		Land info access	−0.1340
		Land info availability	0.5127
		Land private time	0.4322
		Land public time	0.4131
Arb	1.7555	Arbitration laws	0.5412
	(58 %)	Arbitration process	0.6017
		Arbitration judicial	0.5874

characteristics of the data is that it is over-dispersed. The mean number of investments per country is around 10.78, the standard deviation is over 36, i.e. over 3.5 times the mean. A Poisson model implies that the expected count, or mean value, is equal to the variance. This is a strong assumption and does not seem to hold up very well for the data.

Another frequent occurrence with count data is the excess of zeroes compared to what could be expected under a Poisson model. If one were to only analyse non-zero investments, the mean would be higher at 13.31 and the associated standard deviation is just under three times the mean. Also, out of the total 911 possible countries and sectors, around 173 do not receive any investments. It seems therefore that the problem of excess number of zeroes is not widespread in the data.[6]

It is important to check the suitability of the Poisson model with regards to the given dataset. In Table 4.5, Obs refers to the actual observations in the data, and Fit_P and Fit_NB refer to the predictions of the fitted Poisson and the Negative-Binomial models respectively. Whilst 18.99 % of the possible countries and sectors receive no investments, the predictions of the Poisson and the Negative-Binomial models are very close to the true observed values. In fact the Poisson model seems to perform marginally better than the Negative-Binomial model.

[6] To verify that the large number of zeroes do not reflect an underlying always-zero population, I also compute zero-inflated models and find that the results are markedly similar to those of the negative binomial model.

Table 4.5 Characteristics of the data

Variable	#	Mean	Std. dev.	Min.	Max.
Count	911	10.78	36.29	0	620
Count > 0	738	13.31	39.91	1	620
Obs	911	0.1899	0.39	0	1
Fit_P	658[a]	0.1856	0.25	0	1
Fit_NB	658	0.1821	0.23	0	1

[a]The number of observations are lesser than the number of cases in the dataset owing to missing values for some variables in the model

Table 4.6 Poisson model

	(1)	(2)	(3)	(4)	(5)	(6)
Ln.Count existing	0.9586***	0.9589***	0.9716***	0.9823***	0.9813***	0.9937***
	[0.017]	[0.017]	[0.020]	[0.021]	[0.021]	[0.033]
Greenfield	0.0030	0.0031	0.0001	0.0005	0.0004	−0.0016
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Start-up		0.0045	0.0545**	0.0444	0.0206	−0.0550
		[0.036]	[0.028]	[0.028]	[0.038]	[0.069]
Land1			0.0413	0.0457*	0.0602*	0.0434
			[0.032]	[0.027]	[0.031]	[0.037]
Land2				−0.0459	−0.0376	−0.0523
				[0.030]	[0.028]	[0.057]
Arbitration					−0.0477	−0.0468
					[0.044]	[0.092]
Ln.GDP	−0.0762***	−0.0750***	−0.0761**	−0.0807**	−0.0687**	−0.1825**
	[0.026]	[0.027]	[0.035]	[0.033]	[0.034]	[0.089]
Ln.Population	0.0203	0.0172	0.0213	0.0355	0.0313	0.2098*
	[0.025]	[0.034]	[0.052]	[0.045]	[0.043]	[0.116]
Education	−0.0544*	−0.0529*	−0.0662**	−0.0624**	−0.0586**	−0.0838
	[0.031]	[0.030]	[0.029]	[0.029]	[0.029]	[0.055]
Ln.Wages						0.0851
						[0.105]
#	649	649	491	491	491	227
AIC	3,460.1	3,461.9	2,644.2	2,634.3	2,631.1	1,356.5
BIC	3,486.9	3,493.3	2,677.7	2,672	2,673.1	1,394.2

Note: The dependent variable is the count of new investment projects
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

Based on this exploratory analysis, this section will use both Poisson and Negative-Binomial models for the count analysis. The results of these models are presented in Tables 4.6 and 4.7, respectively. In the text, I will concentrate mainly on the results of the Poisson estimation.

In the results provided in Table 4.6, the response variable is 'count' i.e. the number of new investments made within a given sector in a given country. The Poisson regression models the log of the expected count as a function of the predictor variables. More formally, $\beta = \log(\mu_{x+1}) - \log(\mu_x)$, where β is the

Table 4.7 Negative binomial model

	(1)	(3)	(5)	(7)	(9)	(11)
Ln.Count existing	0.8565***	0.8517***	0.8985***	0.9099***	0.9102***	0.9423***
	[0.037]	[0.038]	[0.034]	[0.034]	[0.034]	[0.046]
Greenfield	0.0020	0.0023	0.0011	0.0018	0.0018	0.0014
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.003]
Start-up		−0.0082	0.0410	0.0297	0.0324	−0.1924**
		[0.040]	[0.032]	[0.033]	[0.042]	[0.087]
Land1			−0.0197	−0.0145	−0.0159	−0.0367
			[0.053]	[0.049]	[0.054]	[0.054]
Land2				−0.0590	−0.0610	−0.1680**
				[0.036]	[0.041]	[0.074]
Arbitration					0.0072	−0.0681
					[0.058]	[0.125]
Ln.GDP	−0.0973***	−0.0938***	−0.0776	−0.0766	−0.0780	−0.2735***
	[0.031]	[0.033]	[0.049]	[0.050]	[0.050]	[0.101]
Ln.Population	0.0871**	0.0878*	0.0460	0.0584	0.0592	0.3351**
	[0.039]	[0.053]	[0.076]	[0.075]	[0.075]	[0.149]
Education		−0.0431	−0.0474	−0.0381	−0.0381	−0.0001
		[0.035]	[0.038]	[0.036]	[0.036]	[0.063]
Ln.Wages						0.2966**
						[0.126]
N	658	649	491	491	491	227
AIC	3,121.8	3,075.8	2,341.9	2,339.1	2,341.1	1,205.8
BIC	3,148.7	3,111.6	2,379.6	2,381.1	2,387.3	1,246.9

Note: The dependent variable is the count of new investment projects
*p $<$ 0.1; **p $<$ 0.05; ***p $<$ 0.01

regression coefficient, μ is the expected count and the subscripts represent where the regressor, say x, is evaluated at x and $x + 1$, implying a unit change in the regressor.[7] Since the difference of two logs is equal to the log of their quotient, i.e. $\log(\mu_{x+1}) - \log(\mu_x) = \log(\frac{\mu_{x+1}}{\mu_x})$, thus the parameter estimate can also be interpreted as the log of the ratio of expected counts. In this case, this translates into count referring to the 'rate' of investments by sector and country.

The coefficients can be interpreted as follows. If the count of existing investments were to increase by 1 %, the expected number of new investments would increase by 95.86 % (see model 1 of Table 4.6). As another example, a 1-year increase in the average years of secondary schooling is associated with a 5.4 % fall in expected investments to a country. As the model selection criteria I also examine and compare the Bayesian Information Criterion (BIC) and the Akaike's Information Criterion (AIC). Since the models are used to fit the same

[7] This also implies a unit percentage change for regressors that are in logarithms of the original independent variables.

data, the model with the smallest values of the information criteria is considered better.

The coefficient patterns and statistical significance fit the ex-ante expectations to some extent, but also throw up some interesting results. The first result that pops up from these estimations is the strong and positive effect of existing clusters of foreign direct investment within a country. The results imply that a percentage unit increase in the count of existing investments would increase the expected count of new investments by around 95–98 %, i.e. almost a doubling of expected investment counts. The levels of foreign equity permitted seem to have no statistically significant effect. 'Land1', i.e. the component that reflects better access and availability is seem to be positively associated with the count of new investments, suggesting that land administration systems might have an important role to play in making a country more attractive to new FDI projects. Indeed, 'Land2' the component that broadly reflects the time taken to lease public and private land, seems to be negatively associated with the count of new investments.

The analysis also seems to provide a few surprising results. For instance, 'Arbitration' that is a measure of the strength of the arbitration system seems to be negatively associated with the expected count of new investments, although the effect is not statistically significant.

These specifications control for the total GDP and the population of the country. GDP is negatively associated with the count of new investments, although after controlling for mean manufacturing wages, population is positively associated. Counter-intuitively the average years of secondary schooling seems to negatively affect the expected count of new investments, although the coefficient is no longer statistically significant once wages have been controlled for.

These results remain mostly unchanged within the Negative-Binomial specification (see Table 4.7). The main difference is that the effect of population is now statistically significant in a number of specifications, while wages seem to have positive effect on the expected count of new investments. GDP may have a negative effect on investments if new investments are likely to go towards developing nations – indeed, the coefficient on population might back up this result. I will carry out robustness exercises later in the paper to control for the classification of countries in these and other categories.

4.4.2 Conditional Logit Model

While count data models are able to deal with the assumption of the Independence of Irrelevant Alternatives, and although they are computationally much easier to handle, they have the drawback that it is impossible to analyse more closely the characteristics of the choices made by a given investor. The fDi Markets data, for instance, also provides information on the source country of the investment that allows the possibility of studying clustering of investments by sector and source, in addition to by country. Thus, in this section, I am now able to define three forms of relatedness underlying clustering, investments in the same sector, investments originating in the same country, and investments in the same destination country. Importantly, I am also able to take account of the distance between source and destination countries.

The dependent variable in the conditional logit model will be a binary variable that is associated with the choice made by a foreign investor from a particular country to invest in a particular sector and country. It equals one if a choice is made, and zero otherwise. In addition to the explanatory variables in the count models, the conditional logit model will study two variables: the count of existing investments by source country, and the count of existing investments by sector. In other words, I am interested in controlling for the effect of, say, Japanese investors following previous Japanese investments in a given country, and for the effect of, say, banking projects following previous foreign banking investments. While these clustering variables are interesting in themselves, controlling for them also helps to control for omitted variables bias better – a more detailed description of the possible sources of endogeneity in provided in the next section.

The results of the conditional logit models are presented in Table 4.8. The coefficients can be interpreted as follows: if the percentage of existing investments from the same source country go up by 1 %, then the odds of receiving additional investments would go up by 145 % – see model (1).

What is striking in these results is the prominence of the effects of existing investments. These might refer to the stock of existing investments within a country, or those within a country classified by particular source countries, or by particular sectors – irrespective of the classification, clustering of previous FDI has a strong and positive effect on the odds of new investments.

Ultimately, however, the analysis in interested in the effect of variables that refer to the business and investment climate, after controlling for the effect of previous investments. Some of these results are in line with those observed earlier, while others are very different. For instance, the effect of the components 'Land1' and 'Arbitration' are similar to those of the count models. Land1 has a strong positive and significant effect, suggesting that ease of land administration leasing and information makes countries more likely to receive new investments. Arbitration, which is a measure of the strength and working of the arbitration system in a country, seems to have a negative effect. This would suggest that strong arbitration laws and procedures deter new investments. Although this is an ex-post explanation, this might suggest that countries with more litigious systems might also serve as a deterrent to particular sorts of investments. I re-run the estimations excluding the mining, oil and gas sector, where one might expect a stronger judiciary to deter investments, and find that the results remain stable. Sector-wise results are explored more systematically in the robustness analysis.

It is also surprising that 'Greenfield' which reflects the percentage of foreign ownership of equity permitted, seems to have a negative and statistically significant effect on the choice of new investments. In other words, allowing more foreign ownership within sectors and across countries seems to make the odds of new investments less likely. There could be two trends driving this result – strategic

Table 4.8 Conditional logit model

	(1)	(2)	(3)	(4)	(5)	(6)
Ln.Count existing (country)	0.8573***	0.9383***	0.6792***	0.6591***	0.6751***	0.8458***
	[0.076]	[0.076]	[0.085]	[0.086]	[0.086]	[0.161]
Ln.Count existing (source)	1.4532***	1.4046***	1.4263***	1.4251***	1.4170***	1.5196***
	[0.047]	[0.046]	[0.050]	[0.050]	[0.050]	[0.065]
Ln.Count existing (sector)	0.8497***	0.8666***	0.9845***	0.9792***	0.9618***	0.8617***
	[0.076]	[0.076]	[0.085]	[0.086]	[0.086]	[0.122]
Greenfield	−0.0019**	−0.0021**	−0.0055***	−0.0059***	−0.0062***	0.0036**
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]
Start-up		0.1280***	0.0891***	0.0926***	0.0657***	−0.1989***
		[0.015]	[0.017]	[0.018]	[0.021]	[0.040]
Land1			0.1094***	0.1101***	0.1280***	0.1745***
			[0.015]	[0.015]	[0.017]	[0.025]
Land2				0.0225	0.0357**	0.0547
				[0.016]	[0.017]	[0.039]
Arbitration					−0.0584**	−0.1115
					[0.025]	[0.069]
Ln.GDP	−0.1762***	−0.1569***	−0.2491***	−0.2463***	−0.2300***	−0.2021**
	[0.014]	[0.014]	[0.017]	[0.017]	[0.019]	[0.101]
Ln.Population	0.1375***	0.0564***	0.1928***	0.1877***	0.1808***	0.1748
	[0.012]	[0.016]	[0.022]	[0.022]	[0.022]	[0.133]
Education	−0.2125***	−0.1876***	−0.2293***	−0.2313***	−0.2308***	−0.2341***
	[0.015]	[0.016]	[0.018]	[0.018]	[0.019]	[0.038]
Ln.Wages						0.1155
						[0.092]
Ln.Distance	−0.3108***	−0.3443***	−0.3201***	−0.3179***	−0.3218***	−0.3300***
	[0.016]	[0.017]	[0.019]	[0.019]	[0.019]	[0.025]

Observations	339,159	339,159	219,809	219,809	219,809	67,807
AIC	40,042.9	39,972.1	31,259.3	31,259.4	31,256	16,027.5
BIC	40,128.8	40,068.8	31,362.3	31,372.7	31,379.6	16,146.1

Note: The dependent variable is the choice of new project investment, which is a dummy variable that equals 1 if an investment is made and 0 otherwise
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

sectors that are often accorded higher levels of protection in developing countries remain attractive to investors, and/or that the level of development of countries might be affecting these results. Indeed, once wages (which are a proxy for the cost of labour) are controlled for, the effect is positive.

And finally, in line with the results in the Poisson mode, the results of the conditional logit model seem to suggest that new investments are attracted to markets with smaller GDPs, but larger populations and that higher average years of secondary schooling seem to deter investments. The effects of these variables are positive and statistically significant across almost all specifications. And in line with intuition underlying gravity models, bilateral distances have a strong negative effect on the odds of receiving a new investment.

4.5 Endogeneity Issues and Robustness Exercises

One might be concerned that the coefficients may be biased by two possible sources of endogeneity – reverse causality and omitted variables bias. It could be argued that the presence of FDI within a country might determine certain aspects pertaining to the FDI regime within a given country. In other words, FDI affects business investment environment and not vice versa. However, since the dependent variable refers to *new* investments made within a country, there is little reason to assume that investments made at the margin within a given year might affect the existing investment regime within a given country. This might happen in small countries, where a large investor may be able to directly affect the regime, but the introduction of size effects in all the regressions controls for this. Additionally, lagged values of explanatory variables are also used.

The second problem, which is potentially more serious, is that of omitted variables bias. As an econometrician it is impossible to account for all the characteristics of a country, and one could argue that certain preliminary conditions specific to a country might be affecting all other factors, such as the business climate or existing FDI agglomeration etc. The presence of these unobservables complicates the estimation procedure, since the direction of the bias on the coefficients for the observables is difficult to predict. Ideally, the inclusion of country fixed-effects would deal directly with the problem. However, in the absence of enough time and/or sectoral variation in the data I am unable to use country fixed-effects and thus resort to other alternatives. To deal with the omitted variables bias, and to keep the focus of the analysis on the main variables of interest, I thus include country-level controls and I include the FDI flows over previous years within a country that would be a proxy for all unobservables in the data that might have driven earlier investments. Controlling for existing FDI within a country helps to tease out the marginal effect of the explanatory variables on new investment decisions within a country.

One might also be worried that underestimation of foreign investments across particular sectors or countries might bias these results. For instance, investments made in developing countries might be more sensitive to the general business environment. Alternatively, projects in particular sectors might be underreported. In short, one might want to be certain that the sample selection process is not driving the results. The most direct way to account for such problems would be to interact country and sector fixed-effects, or to use a complete census of investments, small, medium and large. However, owing to the absence of such data and because of the time-invariant nature of the existing data these options are not available. Instead, I carry out three different robustness checks: first, I carry out the estimations and provide the results disaggregated by sector, second, I re-run the estimations disaggregated by different regions, and third, I use census data from a different source to verify if the general results of the analysis still stand.

4.5.1 Sector-Wise Results

I carry out the conditional logit estimations by sector to overcome any bias when the coefficients are constrained to vary across sectors and countries. The disaggregated results provide coefficients that are, by definition, constrained to vary within sectors and across countries and provide the same check as introducing a sector fixed-effect. The coefficients are in the form of odds ratios.

A few interesting results emerge. While clustering by source country and by sector has an overwhelmingly positive affect on the odds of new investments across sectors, that of the total stock of investments within a country seems to have varied effects. Greenfield investments in the banking and light manufacturing sectors seem to be attracted to countries with low proportions of foreign equity in total ownership. This is additional evidence that foreign investments are drawn to strategic sectors that might be protected, but which nevertheless are profitable. Start-up, which reflects the time and procedures taken, is negatively associated with investments in sectors such as transportation, but counter-intuitively with light manufacturing and oil and gas.

Land1, which reflects land leasing, access and availability of information, is consistently and positively associated with the odds of receiving new investments within a country. However, the effect of Land2, that reflects the time taken to lease land, is more ambiguous. In media, it has the expected negative effect, but in light manufacturing it seems to make a country more attractive. And, in line with earlier results, the strength of arbitration laws and procedures in a country seem to dissuade new investments in sectors such as light manufacturing and transportation. And lastly, GDP seems to be negatively associated with the odds of receiving new investments in most sectors, whilst population has a positive effect in sectors such as banking, telecommunications etc. (Table 4.9).

In short, while some of these results differ depending on the sector, they do seem to indicate that for certain sets of variables there is broad consensus. New investments are more likely to follow previous investments, especially by source country and sector. The odds of new investments are positively affected by better

Table 4.9 Conditional logits by sector

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sectors	Banking	CTR	Electricity	LM	Media	MOG	TI	T2
Ln.Country	−0.3842	−0.4000	0.8423*	1.1138***	1.0638	0.6841**	0.3340	0.1373
	[0.326]	[0.447]	[0.461]	[0.247]	[0.891]	[0.278]	[0.216]	[0.621]
Ln.Source	2.0397***	1.8976***	1.2371***	1.3365***	1.2677***	1.4389***	1.2270***	1.2035***
	[0.184]	[0.275]	[0.306]	[0.067]	[0.388]	[0.185]	[0.109]	[0.263]
Ln.Sector	1.2042***	1.0284***	0.5720*	0.7213**	0.7270	0.4999*	1.6031***	1.1264**
	[0.303]	[0.373]	[0.330]	[0.298]	[0.551]	[0.272]	[0.220]	[0.523]
Greenfield	−0.0122***	0.0137	0.0001	−0.0095***	0.0069	−0.0075	−0.0003	−0.0081
	[0.004]	[0.018]	[0.005]	[0.002]	[0.006]	[0.005]	[0.003]	[0.006]
Start-up	0.0168	0.1245	−0.1491	0.1033***	0.0438	0.2230***	−0.0283	−0.2075*
	[0.060]	[0.094]	[0.165]	[0.032]	[0.263]	[0.077]	[0.054]	[0.119]
Land1	0.1263**	0.1145	0.1407	0.1360***	0.0068	0.2167***	0.1588***	0.0414
	[0.058]	[0.097]	[0.119]	[0.022]	[0.167]	[0.072]	[0.045]	[0.080]
Land2	−0.0546	−0.0503	0.0646	0.0939***	−0.2943*	0.0467	−0.0183	0.0753
	[0.054]	[0.094]	[0.126]	[0.025]	[0.154]	[0.078]	[0.044]	[0.076]
Arbitration	0.0262	−0.0767	−0.1942	−0.1284***	0.0750	−0.1352	−0.0198	−0.3006**
	[0.075]	[0.128]	[0.213]	[0.040]	[0.242]	[0.104]	[0.061]	[0.126]
Ln.GDP	−0.1564***	−0.1323	−0.0138	−0.2311***	−0.5227***	−0.4667***	−0.1901***	−0.2943***
	[0.060]	[0.117]	[0.153]	[0.026]	[0.197]	[0.080]	[0.045]	[0.099]
Ln.Pop	0.1357*	0.0950	−0.0906	0.1618***	0.3958	0.4327***	0.2262***	0.2605**
	[0.074]	[0.139]	[0.173]	[0.032]	[0.247]	[0.094]	[0.059]	[0.106]
Education	−0.0392	−0.0140	0.0868	−0.2796***	−0.2788	−0.3252***	−0.2333***	−0.3299***
	[0.058]	[0.112]	[0.112]	[0.026]	[0.193]	[0.092]	[0.044]	[0.103]
Ln.Wages	−0.2249***	−0.2374**	−0.3071**	−0.3973***	−0.7420***	−0.5084***	−0.1008**	−0.3707***
	[0.061]	[0.114]	[0.122]	[0.026]	[0.198]	[0.084]	[0.044]	[0.090]
Ln.Distance	−0.3842	−0.4000	0.8423*	1.1138***	1.0638	0.6841**	0.3340	0.1373
	[0.326]	[0.447]	[0.461]	[0.247]	[0.891]	[0.278]	[0.216]	[0.621]

#	19,390	6,619	4,728	125,133	1,876	10,472	41,847	9,207
AIC	2,883.9	1,039.2	779.1	17,287.8	326.6	1,578.3	5,656.2	1,418.2
BIC	2,978.4	1,120.8	856.7	17,404.6	393.1	1,665.3	5,759.9	1,503.8

Notes: *CTR* construction tourism and retail, *LM* light manufacturing, *MOG* mining gas and oil, *T1* telecommunications, *T2* transportation. Concordance was not achieved for HW with the inclusion of pair-wise distance data and so the regression was run without this variable

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

access and availability of land leasing information, lesser time taken to start-up and larger size of the country (proxied by population). And in all cases, country-pair distance seems to deter investments.

4.5.2 Region-Wise Results

Since the lack of variation in the data does not allow me to control for country fixed-effects, I also divide my sample by different country classifications to see how the results differ and to what extent they hold. I use two different regional classifications – by geography and by income. The first set of regions are based on geography – East Asia and Pacific (EAP), Europe and Central Asia (ESA), Latin America and the Caribbean (LAC), Middle East and North Africa (MENA), South Asia (SA) and Sub-Saharan Africa (SSA). The income classification is based on 2010 Gross National Income per capita: Low-Income Economies ($1,005 or less), Lower-Middle Income Economies ($1,006–$3,975), Upper-Middle Income Economies ($3,976–$12,275), and High-Income Economies ($12,276 and above). The results by region are presented in Table 4.10 and by income are presented in Table 4.11. Note that some explanatory variables are dropped in specifications owing to inadequate observations.

The results for the regional specifications show that clustering by country, source and sector, all seem to positive affect the likelihood of receiving new investments. The high coefficient for sectoral clustering in the MENA and the SSA regions might indicate that foreign investments are directed towards a few sectors. The percentage of foreign ownership seems to have little or no effect on new investments. The time or procedures taken to start-up seem to negatively affect the odds of new investments in the ESA region. Land leasing, access and availability consistently has a positive effect, although the effect of Land2, which is a rough measure of time taken to lease, varies across regions. The strength of arbitration, just as in earlier specifications, continues to have a negative effect. And lastly, it is clear that the rate of growth of GDP per capita has a strong positive effect in where there are concentrations of emerging economies, such as the SA and the LAC regions.

I also slice the data by income levels and then re-estimate the conditional logits. The results for clustering are broadly similar, wherein source and sectoral clustering are important across most regions. It is interesting however, that the foreign ownership levels have a negative effect on the odds of new investments in lower-middle income countries, but a positive effect in high-income countries. This suggests that foreign investments are more likely to be drawn to developing countries when there are stricter limits to foreign ownership, but to developed countries if these limits are lower. This again could be driven by the protection of policy of protecting strategic sectors in many emerging economies, which might also be sectors of much interest to FDI.

Start-Up seems to positively affect investments in most regions – indeed, its effect in lower-middle and higher-middle income countries is the strongest, while it has a negative effect on investments in Europe and central Asia. Land1 affects new

Table 4.10 Conditional logits by geography

	EAP	ESA	LAC	MENA	SA	SSA
Ln.Count existing		0.8941***	0.8848***			−1.9461
		[0.195]	[0.232]			[1.478]
Ln.Count existing (source)	1.3479***	1.3423***	1.3795***	1.3992***	0.5625	−0.0636
	[0.348]	[0.091]	[0.080]	[0.540]	[0.377]	[0.591]
Ln.Count existing (sector)	2.0926***	0.8541***	0.1219	2.9893**	−0.6550	3.1123**
	[0.390]	[0.145]	[0.160]	[1.187]	[0.465]	[1.569]
Greenfield	0.0071	0.0043*	−0.0009	−0.0118	0.0000	−0.0056
	[0.007]	[0.002]	[0.003]	[0.012]	[0.011]	[0.017]
Start-up		−0.0924**	0.1200**			0.3098
		[0.042]	[0.061]			[0.280]
Land1		0.1405***	0.3372**			
		[0.026]	[0.136]			
Land2	−0.1404**	0.0082	0.5001***	−0.2543	1.2347***	−0.2378
	[0.066]	[0.039]	[0.148]	[0.462]	[0.328]	[0.440]
Arbitration		−0.1030	−0.0270			
		[0.072]	[0.087]			
Ln.GDP	−0.0014	−0.0540	−0.2659**	−1.1594	2.3913***	
	[0.039]	[0.065]	[0.113]	[1.105]	[0.604]	
Ln.Population		0.0373	0.3177*		−1.6659***	−0.2339
		[0.079]	[0.178]		[0.568]	[0.391]
Education		−0.1884***	−0.1192			
		[0.034]	[0.155]			
Ln.Wages	−0.3721	−0.4274***	−0.5529***	−0.3908	0.3497	0.4704
	[0.272]	[0.052]	[0.058]	[0.354]	[0.890]	[1.896]
Ln.Distance		0.8941***	0.8848***			−1.9461
		[0.195]	[0.232]			[1.478]
Observations	1,314	42,684	22,199	280	1,840	116
AIC	884.1	11,308.9	5,355	131.3	337.9	71.86
BIC	915.2	11,412.9	5,451.1	153.1	376.5	93.89

Note: The dependent variable is the count of new investment projects
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

investments positively in high-income countries and in the ESA and LAC regions. Land2, on the other hand, negatively affects investments in the EAP region, but positively in the LAC and SA region, and in lower-middle income countries.

The results for arbitration are interesting. Well-functioning arbitration systems make lower-middle and upper-middle income countries very attractive to new investments, but the opposite result is observed for high-income countries. This clearly indicates that better arbitration is better for investment, but it might be possibly that especially litigious systems might be turning investors away. And in line with the other results, the size of GDP in high-income countries makes them less attractive to new investments, while the size of the population has the opposite result. In all these results, education and distance seem to play a negative role.

Table 4.11 Conditional logits by income

	High-income	Low-income	Lower-middle income	Upper-middle income
Ln.Count existing	0.3679**		1.0697	1.0663***
	[0.167]		[0.657]	[0.143]
Ln.Count existing (source)	1.2149***	1.3265	1.4419***	1.3388***
	[0.105]	[1.069]	[0.207]	[0.065]
Ln.Count existing (sector)	0.8436***	0.1739	0.7553**	0.7628***
	[0.153]	[1.116]	[0.317]	[0.130]
Greenfield	0.0031*	0.0039	−0.0095*	−0.0018
	[0.002]	[0.036]	[0.005]	[0.003]
Start-up	−0.2943***	−4.6954	0.4277**	0.2413***
	[0.048]	[4,947.514]	[0.184]	[0.039]
Land1	0.2518***		0.0907	−0.0193
	[0.044]		[0.132]	[0.055]
Land2	−0.0237	3.3508	0.4219***	−0.0415
	[0.035]	[3,431.231]	[0.140]	[0.046]
Arbitration	−0.1786**		0.4113*	0.0941**
	[0.072]		[0.371]	[0.060]
Ln.GDP	−0.2312**		−0.6783	−0.0803
	[0.101]		[0.641]	[0.177]
Ln.Population	0.4272***		0.2454	−0.1270
	[0.118]		[0.401]	[0.208]
Education	−0.1706***	−2.5746	−0.0389	−0.4260***
	[0.029]	[3,436.657]	[0.139]	[0.051]
Ln.Wages	−0.2949***	−0.1270	−0.6821***	−0.5489***
	[0.027]	[0.681]	[0.181]	[0.037]
Ln.Distance	0.3679**		1.0697	1.0663***
	[0.167]		[0.657]	[0.143]
Observations	29,652	75	6,152	39,028
AIC	9,773.9	52.82	1,183.8	9,547.5
BIC	9,873.4	69.05	1,264.5	9,650.4

Note: The dependent variable is the count of new investment projects
*p < 0.1; **p < 0.05; ***p < 0.01

4.5.3 BEA Results

As a third robustness check, I also re-run the earlier analysis this time using a different source of data. I collect data on US multinational companies' new manufacturing investments from the US Bureau of Economic Analysis (BEA). Owing to data availability, the census is restricted to the year 2008, and again, only investments that are larger than US$40 million are accounted for. In other words, the data covers setting up of new, albeit only very large, manufacturing affiliates. In addition, the data covers global investments and data is available for over 220 countries. The total number of new foreign affiliates set up by US companies in 2008, of the value of US$40 million and over, was 170. Since the source country remains the US, the variation in the data comes from investments made across sectors and countries.

I run two different sets of models, count (Poisson) and conditional logit for verification. The results of the analysis are presented in the form of incidence rate ratios and odds ratios, respectively in Table 4.12. Columns (1–6) present the results of the step-by-step Poisson model, and column (7) provides the results of the conditional logit model. When comparing these results to those from earlier specifications based on fDi Markets data, it should also be kept in mind that these results provide information on the behaviour of mainly American investments abroad.

The results provide further evidence for the strong effect of existing investments within a country. American investors, just as their counterparts, are more likely to make new investments in countries where other US investors have previously favoured. American investors also seem to favour sector and countries which have more restrictions on foreign equity ownership – this is in line with some of the earlier results from the fDI markets database. Additionally, the effect of the number of Start-up has a negative and statistically significant effect across some Poisson specifications, suggesting that US foreign affiliates are deterred from investing in countries with cumbersome procedures for starting new subsidiaries.

What is different here is the effects of Land1 and Land2 – while the former has no statistically significant effect, the former has a strong positive effect. Since Land2 is to some degree an indication of the time taken to lease private and public land, this is a surprising result. The size of the market, given by both the GDP and the population of a country positively affects American investments into a country, although neither variable is significant with the conditional logit model. The positive coefficient on GDP makes American investors different from the earlier sample, and this result is also borne by the coefficient on wages, which is positive – again suggesting that American investments are drawn to developed markets. In summary, although some of these results are robust across earlier specifications, it does seem that investors from particular countries might have marginally different factors that underlie their investments decisions.

4.6 Conclusion

This paper attempts to answer the following question: To what extent does the quality of FDI regulations and investment policy within a country affect its likelihood of attracting new foreign investors? It is also interested in parcelling out the effect of existing clusters of foreign investments within a country – in other words, I also want to account for the effect of the existing stock of FDI. Given that certain geographical locations clearly attract a disproportionate share of FDI activity, it is crucial to understand what features drive this success. The

Table 4.12 Robustness (BEA data)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ln.Count existing	1.0811***	1.0414***	1.0296***	1.0087***	0.9851***	0.9867***	1.8688***
	[0.092]	[0.088]	[0.092]	[0.092]	[0.092]	[0.136]	[0.372]
Greenfield	−0.0072**	−0.0059	−0.0039	−0.0024	0.0001	−0.0011	−0.0006
	[0.004]	[0.004]	[0.004]	[0.004]	[0.005]	[0.006]	[0.006]
Start-up		−0.2219*	−0.2605*	−0.2018	−0.1882	−0.9938***	−0.1019
		[0.122]	[0.143]	[0.145]	[0.146]	[0.301]	[0.124]
Land1			0.0276	0.0603	0.0646	0.1321	0.0084
			[0.133]	[0.140]	[0.136]	[0.172]	[0.107]
Land2				0.3552***	0.3872**	0.2457	0.1983*
				[0.135]	[0.173]	[0.184]	[0.105]
Arbitration					−0.0579	−0.2936	0.0629
					[0.275]	[0.740]	[0.171]
Ln.GDP	0.4879***	0.4277***	0.4646***	0.4225***	0.4650***	−1.5139	0.0735
	[0.142]	[0.123]	[0.135]	[0.117]	[0.158]	[0.974]	[0.158]
Ln.Population	0.2458*	−0.0408	−0.1595	−0.1850	−0.2277	1.5491*	−0.0564
	[0.139]	[0.160]	[0.193]	[0.159]	[0.220]	[0.918]	[0.168]
Education	0.0246	−0.0250	0.0181	0.0082	0.0046	0.1957	0.1696
	[0.137]	[0.136]	[0.123]	[0.106]	[0.111]	[0.208]	[0.117]
Ln.Wages						2.2205**	
						[0.930]	
Ln.Distance							−0.1284
							[0.097]
#	528	528	440	440	440	161	4,022
AIC	536.7	527.7	443	433.1	434	200.4	803.7
BIC	562.3	557.6	475.7	469.8	478.9	234.3	866.7

Note: The dependent variable is the count of new investment projects
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

importance of this research is underscored by two inter-related factors – previous FDI inflows can have important implications for economic development, especially in developing countries, and that the contribution of foreign investors could make their presence a potent tool in the hands of governments in influencing economic policy.

The empirical findings of the analysis provide evidence for the impact of different aspects of the investment climate within a country that seem to be affecting investment decisions at the margin. I find that making it unwieldy for foreign investors to start a subsidiary doesn't necessarily deter them from investing, that better land leasing, more access and availability of information on land encourages investment, that in some cases making it more difficult and time-consuming to lease public land discourages investment, and that arbitration systems can matter in particular regions where legal institutions might be weak. In short, investment policies matter.

One of the most robust empirical finding of the paper is that clustering, whether by country, source or sector seems to matter strongly for new investors, indicating that path dependence has important implications for new FDI flows. Additionally, the robustness analysis also reveals how investors' choices can different depending on the sector and the region in question. This is an indication that netting out the effect of sectors and country effects, an exercise which could not be carried out in this paper owing to lack of adequate variation in the data, might provide interesting results.

There are certain limitations to what can be concluded from the analysis. In the absence of adequate data, the paper is unable to test to what extent firm-level characteristics are driving investment decisions. Whilst theoretical models would predict that the most productive firms would self select into engaging in FDI, they do not shed light upon what sort of markets they might choose to invest in. Even with more data on individual investors, we might be hard pressed to explore cross-country location decisions.

Additionally, endogenity issues usually plague the use of cross-sectional analysis. However, in this case, since the impact of institutions within a country can be persistent over time, often using within-country time series data to identify the impact of such effects can be difficult. This analysis overcomes this problem by concerning itself with the effect of these institutions across countries, demonstrating that cross-country comparisons can be informative.

The conclusions and results presented in this analysis are in line with reason and intuition. This exercise provides consolidating evidence for policy-makers about how to attract investors. In addition, the research has filled a big gap in the existing empirical literature about factors that matter to big investments across national borders. In particular the analysis takes into account the variable influence of economic geography, economic, institutional and judicial factors. In the absence of standardised and comparable data, theories regarding the overlapping effects of such factors have previously not been verified using robust methodological approaches. This paper has provided empirical backing to guide governments' policy choices aimed at attracting new foreign direct investments.

Appendix: Industry Concordances

IAB	FDI markets	BEA
Agriculture & forestry		1110; 1120; 1130; 1140; 1150
Banking	Financial services	5221; 5223; 5224; 5231; 5238; 5242; 5243; 5249; 5252
Construction, tourism and retail	Building & construction materials; hotels & tourism	4410; 4420; 4431; 4440; 4450; 4461; 4471; 4480; 4510; 4520; 4530; 4540; 2360; 2370; 2380
Electricity	Alternative/renewable energy	2211; 2212; 3336
Health and waste	Healthcare	2213; 5620; 6210; 6220; 6230; 6240
Light manufacturing	Automotive components; beverages; biotechnology; business machines & equipment; ceramics & glass; chemicals; consumer electronics; engines & turbines; food & tobacco; industrial machinery, equipment & tools; medical devices; paper, printing and packaging; pharmaceuticals; plastics; rubber; semiconductors; textiles; wood products	3111; 3112; 3113; 3114; 3115; 3116; 3117; 3118; 3119; 3121; 3122; 3130; 3140; 3150; 3160; 3210; 3221; 3222; 3231; 3256; 3259; 3322; 3326; 3254; 3261; 3262; 3271; 3272; 3273; 3274; 3279; 3311; 3312; 3314; 3315; 3321; 3323; 3324; 3325; 3327; 3328; 3329; 3331; 3332; 3333; 3334; 3335; 3336; 3342; 3343; 3344; 3345; 3346; 3351; 3352; 3353; 3361; 3362; 3363; 3364; 3365; 3366; 3369; 3370; 3391; 3399
Media	Leisure & entertainment	5111; 5112; 5121; 5122; 5151; 5152
Mining, oil and gas	Coal, oil and natural gas; metals; minerals	2111; 2121; 2123; 2114; 2115; 2116; 2117; 2132; 2133; 3244; 3243; 3242; 4863; 4868
Telecommunications	Communications; software & IT services	5171; 5172; 5174; 5179; 5182; 5191
Transportation	Aerospace; transportation	3361; 3363; 3364; 3365; 3366; 3369; 4810; 4821; 4833; 4839; 4850; 4863; 4880

Notes: *IAB* investing across borders, *BEA* bureau of economic analysis

References

Blonigen BA (2005) A review of the empirical literature on FDI determinants, NBER working paper no. 11299. NBER, Cambridge, MA

Blonigen BA, Ellis CJ, Fausten D (2005) Industrial groupings and foreign direct investment. J Int Econ 65:75–91

Bobonis GJ, Shatz HJ (2007) Agglomeration, adjustment, and state policies in the location of foreign direct investment in the United States. Rev Econ Stat 89(1):30–43

Brainard SL (1997) An empirical assessment of the proximity–concentration trade-off between multinational sales and trade. Am Econ Rev 87:520–544
Carlton D (1979) Why new firms locate where they do: an econometric model. In: Wheaton W (ed) Interregional movements and regional growth. Urban Institute, Washington, DC
Carstensen K, Toubal F (2004) Foreign direct investment in Central and Eastern European countries: a dynamic panel analysis. J Comp Econ 32:3–32
Coughlin CC, Segev E (2000) Foreign direct investment in China: a spatial econometric study. World Econ 23(1):1–23
Guimaraes P, Figueiredo O, Woodward D (2000) Agglomeration and the location of foreign direct investment in Portugal. J Urban Econ 47(1):115–135
Guimaraes P, Figueiredo O, Woodward D (2003) A tractable approach to the firm location decision problem. Rev Econ Stat 85(1):201–204
Guimaraes P, Figueiredo O, Woodward D (2004) Industrial location modeling: extending the random utility framework. J Reg Sci 44(1):1–20
Head CK, Ries JC, Swenson DL (1995) Agglomeration benefits and location choice: evidence from Japanese manufacturing investments in the United States. J Int Econ 38:223–247
Head CK, Ries JC, Swenson DL (1999) Attracting foreign manufacturing: investment promotion and agglomeration. Reg Sci Urban Econ 29(2):197–218
Helpman E (1984) A simple theory of international trade with multinational corporations. J Polit Econ 92(3):451–471
Helpman E, Krugman P (1985) Market structure and foreign trade. MIT Press, Cambridge, MA
Helpman E, Melitz MJ, Yeaple SR (2004) Export versus FDI with heterogenous firms. Am Econ Rev 94(1):300–316
Hines JR (1995) Forbidden payment: foreign bribery and American business after 1977, NBER working paper no. 5266. NBER, Cambridge, MA
Lankhuizen M, De Groot HLF, Linders GM (2011) The trade-off between foreign direct investments and exports: the role of multiple dimensions of distance. World Econ 34:1395–1416
Markusen JR (1984) Multinationals, multi-plant economies and the gains from trade. J Int Econ 16:205–226
Markusen JR (1997) Trade versus investment liberalisation, NBER working paper no. 6231. NBER, Cambridge, MA
Markusen JR (2002) Multinational firms and the theory of international trade. MIT Press, Cambridge, MA
Markusen JR, Venables AJ (1998) Multinational firms and the new trade theory. J Int Econ 46(2):183–203
Mataloni R (2009) Do US multinationals engage in sequential choice? Evidence from new manufacturing operations in Europe. In: Cornejo LK (ed) Multinational companies: outsourcing, conduct and taxes. Nova, New York
McFadden D (1974) Conditional logit analysis of qualitative behaviour. In: Zarembka P (ed) Frontiers in econometrics. Academic, New York, pp 105–142
Mukim M, Nunnenkamp P (2012) The location choices of foreign investors: a district-level analysis in India. World Econ 35(7):886–918
Nunnenkamp P, Mukim M (2012) The clustering of FDI in India: the importance of peer effects. Appl Econ Lett 19(8):749–753
Resmini L (2000) The determinants of FDI in the CEECs: new evidence from sectoral patterns. Econ Transit 8(3):665–689
UNCTAD (1998) World Investment Report 1998. United Nations, New York/Geneva
Wei S-J (2000) How taxing is corruption on international investors? Rev Econ Stat 82(1):1–11
Wheeler D, Mody A (1992) International investment location decisions: the case of U.S. firms. J Int Econ 33(1):57–76

Chapter 5
External Effects of Metropolitan Innovation on Firm Survival: Non-Parametric Evidence from Computer and Electronic Product Manufacturing and Healthcare Services

Alexandra Tsvetkova, Jean-Claude Thill, and Deborah Strumsky

5.1 Introduction

In the last two decades, geography came into prominence as an important consideration in the study of knowledge accumulation, firm performance, and economic growth. The role of space as a determinant of economic outcomes comes primarily from the non-uniform distribution of human and social capital across territories. Accumulated knowledge, specific in each region, eventually should translate into productive applications and lead to dissimilar rates of economic growth (Ibrahim et al. 2009). The literature argues that knowledge, innovativeness, and entrepreneurship (factors that in the short-run are 'attached' to a region) play a definite role in economic outcomes.

Despite the widely held view echoed in the agglomeration theory that external knowledge and innovation are important for firm performance in general, and business survival in particular, empirical evidence on this issue is lacking. No study has so far provided empirical insights into the relationship between regional innovative environment and firm longevity, although the perspective of regional innovative systems seems to have gained popularity in the last few years (Rodriguez-Pose and Crescenzi 2008; Uyarra 2010).

External effects of innovation on firm survival are not straightforward. The agglomeration literature suggests that accumulated regional stock of knowledge should contribute to business productivity and innovation in a region. The survival literature consistently finds a positive relationship between a firm's own

A. Tsvetkova (✉)
School of Public Policy, George Mason University, 3351 Fairfax Dr, Arlington, VA 22201, USA
e-mail: atsvetko@gmu.edu

J.-C. Thill • D. Strumsky
Department of Geography and Earth Sciences, University of North Carolina – Charlotte, 9201 University City Boulevard, Charlotte, NC 28223, USA
e-mail: Jean-Claude.Thill@uncc.edu; dstrumsk@uncc.edu

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productivity and firm survival. It seems there is a reason to believe that regional innovation is positively related to business longevity at a regional level. This perspective, however, does not take into account increased competition in the regions with more innovative economies, the so-called ‘creative destruction’ regime advanced by Schumpeter (1942). According to this other approach, the net effect of regional innovation on firm survival within the same region would be expected to be negative.

Using non-parametric duration analysis, this study empirically tests the impact of innovative environments on survival likelihood of individual non-patenting firms in two industrial sectors, namely computer and electronic product manufacturing, and healthcare. These sectors represent the high technology end of the U.S. economy, which is crucial for the economic competitiveness of the country. The analysis assesses the intervening effect of three regional properties, namely the rate of new firm creation in the sectors of interest, business density, and population density.

5.2 Why Is Space Important?

Over the last decades, an extensive body of literature has emphasized the importance of geography as a significant determinant of industrial performance. Regions influence innovation, firm entry, learning, and economic growth (Scott 2006). The importance of space for regional economic performance is not a new idea. Back in the 1920s, Marshall articulated the advantages of locational externalities associated with geographically dense networks of suppliers and customers, the character of the local labor pool, and pure spillovers from one business to another, which allow firms to become more innovative by employing (modified) designs and concepts of their peers (Ibrahim et al. 2009).

Much in line with Marshall’s argument on co-location, the new economic geography, or NEG (Krugman 1991), explains the emergence and persistence of large urban agglomerations that rely on reduced transportation costs, increasing returns to scale, and benefit from interactions of closely related suppliers and consumers (Schmutzler 1999). The intra-industry economies of localization, elaborated in the NEG, may occur through (1) economies of specialization; (2) labor market economies; and (3) knowledge spillovers (Breschi and Lissoni 2001). The agglomeration effects are hypothesized to increase labor productivity and innovativeness of individual firms (Henderson et al. 2001; Porter 1990) in two primary ways. The first assumes that nearness is able to influence economic outcomes by the sole virtue of being a part of a spatial business concentration leading to economies of scale (Gordon and McCann 2000). The second views proximity as a facilitating condition for the exchange of resources among firms (Knoben and Oerlemans 2006).

Extensive empirical literature supports positive effects of agglomeration on the regional and firm-level economic performance. For instance, Rodriguez-Pose and

Comptour (2012) argue that industrial clusters, if they happen to form in the areas with highly trained and educated labor force, promote economic growth in European regions. Lehto (2007) finds that closeness has a positive impact on productivity in a sample of Finnish firms.

A related concept that links regions and economic growth through knowledge creation and innovation is regional innovation systems or RIS (Uyarra 2010). It starts with the proposition that '[i]nnovation is a territorially embedded process and cannot be fully understood independently of the social and institutional conditions of every space' (Rodriguez-Pose and Crescenzi 2008, p. 54). Here, territorial actors and institutions are hypothesized to play an important role in regional growth. The competitive advantages of regions are also related to the institutional characteristics such as the level and structure of education and R&D activities, available financial services and so forth (Cassia et al. 2009). Regional innovative systems should enable regions to adjust to the existing conditions in a way that promotes sustained regional growth. Recent literature emphasizes that production and utilization of knowledge is a primary way to do so. Therefore, knowledge and the spillovers associated with it are essential for regional economic development process (Stough and Nijkamp 2009).

5.3 Firm Survival: The Role of Knowledge and Space

As pointed out, it is almost a convention in the literature that accumulated local knowledge should translate into superior firm performance. Extensive research on local knowledge spillovers describes in great detail why this relationship is expected to hold and provides vast empirical evidence to support this claim. Ibrahim and co-authors (2009, p. 412, italics in original) define knowledge spillovers as the 'useful *local sources* of knowledge found in a region, that were obtained beyond the recipient's organization, and that affected the innovation of the recipient'. The spillover literature models knowledge as a public good, which is at least partially non-rival and non-excludable. Knowledge tends to accumulate in spatially bounded areas and requires some sort of interactions to spread. The intensity of knowledge spillovers declines with distance (Adams and Jaffe 1996; Bottazzi and Peri 2003; Rodriguez-Pose and Crescenzi 2008; Wang et al. 2004). Firms located in areas with intensive research by business and/or universities are expected to be more inventive and productive even when they do not participate in formal research activities (Koo 2005; Zachariadis 2003).

With respect to firm survival, though, presence of local knowledge spillovers is likely to have divergent effects. On the one hand, firms may learn from others in order to become more productive and efficient. In this case, businesses operating in the areas with greater stock of knowledge should live longer. On the other hand, agglomeration of businesses in a particular geographical area may be detrimental to firms located there. Congestion and increased competition, common attributes of agglomerations, may lead to firm failure and exit.[1] According to Schumpeter (1942), in the markets with active entry, incumbents are more likely to exit. It happens because firms are usually innovative during the initial stages of their development when they try to find a niche in the market. After a firm stops introducing novelties, it loses entrepreneurial character and is likely to exit, just as new innovative firms keep bringing new knowledge-rich combinations to the economy. The process through which more innovative firms drive less innovative ones out of business is the nature of 'creative destruction'. Thus, more innovative regions should experience greater 'creative destruction', i.e. a greater number of firms entering and exiting the market, which is a necessary condition of development and increased productivity (Bosma et al. 2011).

Effects of agglomeration and proximity to urban areas are perhaps the most studied regional determinants of business survival. The empirical evidence up to date is mixed. Access to a labor pool of higher quality, proximity to suppliers, consumers and other firms is likely to improve the business prospects of a firm (Strotmann 2007), its productivity and innovation (Stephan 2011). Fotopoulos and Louri (2000) report a positive impact of proximity to Athens on the survival rates in the Greek manufacturing sector. In the United States, Buss and Lin (1990) find no difference between firm survival rates in urban and rural areas; while Renski (2009) concludes that firms located in an urban core are more likely to exit. Another study shows that firms located close to the capital in Austria enjoy survival rates comparable to those of other firms throughout the country (Tödtling and Wansenböck 2003). A few studies find insignificant or very limited impact of proximity to urban areas (Globerman et al. 2005; Littunen 2000). At the same time, overcrowding, higher rent and wage level may translate into shorter expected lifespan (Headd 2003; Strotmann 2007). The observed relationship usually depends on industry, region, and other conditions. For example, urbanization promotes firm longevity in two U.S. industries (computer and data processing and measuring, and controlling devices) but increases hazard in two others (drugs, and farm and garden machinery) (Renski 2011).

An alternative measure of urbanization, population density, can have positive (Fertala 2008; Wennberg and Lindqvist 2010), negative (Brixy and Grotz 2007; Fritsch et al. 2006), and insignificant effect on firm longevity. Acs et al. (2007) find that the ratio of business intensity to population density increases chances of firm survival in the U.S. Labor Market Areas. Investigation of U.S. manufacturing shows a complex relationship between population density, firm survival, order of entry, and industry life cycle. A U-shaped relationship between density and survival

[1] Abstracting from local knowledge spillovers, greater stock of knowledge in a region may contribute to a greater likelihood of exit via at least two other routes. The knowledge spillover theory of entrepreneurship postulates that more knowledge being produced (and unutilized) in a region should increase firm formation, thus increasing competition. At the same time, in the localities where more knowledge is generated, the incumbent firms are likely to be exposed to more business ideas. Firm owners might choose to sell off or to shut down their business in order to start something new that looks more promising.

exists during the growth phase of an industry. In mature phases, this relationship holds only for mature phase entrants. The relationship is insignificant for growth phase entrants (Agarwal et al. 2002).

Industrial specialization and industrial diversity are two additional regional characteristics potentially related to business survival that merit more attention from scholars. Renski (2011) shows that industrial specialization of a region is associated with lower exit probability in a number of U.S. industries. The opposite of regional specialization and a proxy for Jacobian externalities, industrial diversity, extends expected firm lifespan in knowledge-intensive industries in the U.S. (Renski 2011).

Other regional factors of firm survival are still ill-understood (Brixy and Grotz 2007; Fertala 2008; Fritsch et al. 2006; Manjon-Antolın and Arauzo-Carod 2008). Regional characteristics are likely to have complex effect on firm survival. By facilitating a more efficient business performance that may be conducive to greater longevity, they are likely to intensify competitive pressure, which increases the likelihood of exit (Stuart and Sorenson 2003). In addition, regional traits are likely to affect business survival indirectly via other variables; however, the ability of regional characteristics to shape firm performance depends on the industry (Broekel and Brenner 2011), and the specific level of firm operation (Acs et al. 2009).

5.4 Logical Models and Estimation Approach

The agglomeration literature implies that knowledge spillovers may increase business productivity. Research on business survival has posited that productivity has a negative effect on the hazard faced by firms. Figure 5.1 shows schematically a simplified logical model of this relationship.

On the other hand, innovation in a region may intensify competition and facilitate exit. This mechanism, described by Schumpeter (1942) as ‘creative destruction’, is presented in Fig. 5.2.

As the discussion above indicates, effects of regional innovation on business longevity may be both positive and negative depending on the theoretical arguments of regional economics. In this chapter, we use non-parametric survival analysis (Elandt-Johnson and Johnson 1999; Cleves et al. 2010) to explore the relationship between innovation in a metropolitan region and the hazard faced by firms located there. The non-parametric approach allows us to track and visualize the main associations in the data without imposing assumptions of specific functional distributions of the variables, or failure times. To conduct the analysis, we classify all the firms in the sample into three groups according to the level of innovation and knowledge creation in the metropolitan region where each firm is located. Next, using the Peto-Peto-Prentice test, we compare the survival functions of the firms located in metropolitan areas with low, medium, and high levels of innovation in general. To control for the anticipated intervening effect of some metropolitan characteristics, we also subdivide the firms depending on three critical

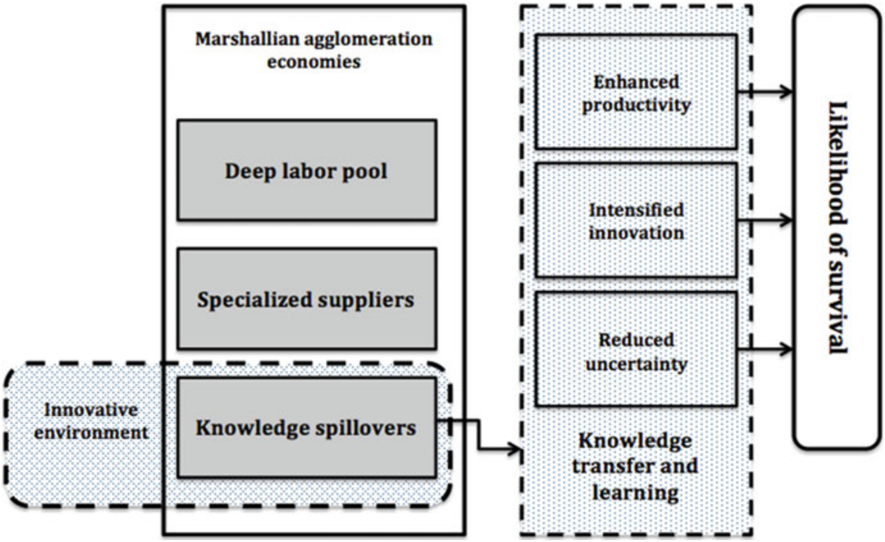

Fig. 5.1 Schematic representation of the relationship between innovation and firm survival as it follows from the literature on knowledge spillovers

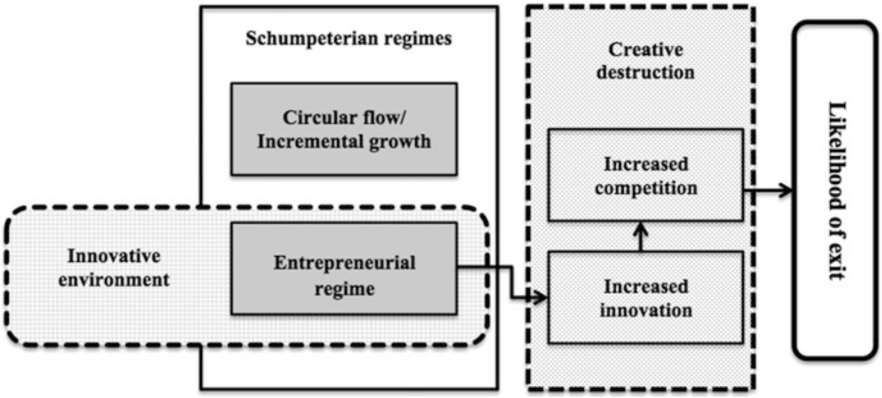

Fig. 5.2 Schematic representation of the relationship between innovation and firm survival as it follows from the literature on creative destruction

variables, namely the number of new firms in the industrial sectors of interest (firm creation), and two measures of urbanization (business density and population density). We then repeat the Peto-Peto-Prentice test for each subset of metropolitan regions corresponding to each of the three possible levels defined on each one of these variables, in turn. Finally, we graph the smoothed hazard estimates for each subgroup to gain better insight in firm survival dynamics over time and to contrast the subgroups in relation to metropolitan innovation levels.

5.5 Industries and Establishments

The effects of the innovative environment on firm survival is expected to differ across industries (Audretsch 1995). Highly innovative industries, which employ people inclined to pick up new ideas from their surrounding and to promptly introduce them into practice, are likely to be more perceptive to the overall innovativeness of a geographic region. Likewise, industries with a production process that allows quick implementation of innovations and experimenting without excessive sunk costs should be expected to benefit more from the level of invention in an area. Other industries, due to the individual specificities, might be less sensitive to the 'innovative atmosphere'. In addition, industry often determines the intensity of local knowledge spillovers (Glaeser et al. 2002).

At the same time, a competition regime is likely to be unique to every industry, as should be the impact of innovation on firm longevity via competition (Fritsch et al. 2006; Segarra and Callejón 2002). This necessitates testing for external effects of innovation on business life expectancy separately by industry. To encompass both manufacturing and service ends of the U.S. economy, we study a high-technology manufacturing (HTM) sector (represented by computer and electronic product manufacturing), and a high-technology service (HTS) sector (represented by healthcare services). Focus on high-technology sectors is determined by their substantial contribution to the national welfare and growth (Koo 2005). The list of industries in each sector identified by 4-digit NAICS codes is given in Table 5.1.

Using the National Establishment Time Series (NETS) Database,[2] we identify all establishments[3] that belong to the selected industries and are set up in the continental U.S. Metropolitan Statistical Areas (MSAs) in year 1991. An establishment is assumed to be alive until the last year it is recorded in the NETS Database (YEARLAST). We track the selected companies until the last year in the database or year 2008, whichever happens first. As a result, there are up to 17 observations for each firm. Only standalone non-patenting firms that did not exit via merger or acquisition during the study period are included in the sample.[4] Firms with more than 100 employees in year 1992 were also excluded for control purposes. The final sample includes 1,614 computer and electronic manufacturing firms and 1,414 healthcare services firms.

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[2] A more detailed description of the data sources used is given in the next section.

[3] The NETS Database includes records of all establishments (not firms or companies) reported by Dun & Bradstreet. It has relationship indicators, which identify a headquarter organization for each establishment. Only stand-alone establishments (DUNS Number, primary Database identifier, is the same in ID and HEADQUARTER fields of the NETS Database) are included in the estimation; therefore, the terms 'establishment,' 'firm,' and 'company' are used interchangeably.

[4] The NETS Database indicates standalone establishments. The U.S. PTO database was used to determine if a firm in the sample had at least one successful application before year 2009. The Deal Pipeline, Alacra Store, and Wharton Research Data Services provided information on mergers and acquisitions.

Table 5.1 Industries included in each sector

Code	Industry
High-technology manufacturing sector (HTM)	
NAICS3341	Computer and peripheral equipment manufacturing
NAICS3342	Communications equipment manufacturing
NAICS3343	Audio and video equipment manufacturing
NAICS3344	Semiconductor and other electronic component manufacturing
NAICS3345	Navigational, measuring, electromedical, and control instruments manufacturing
NAICS3346	Manufacturing and reproducing magnetic and optical media
High-technology service sector (HTS)	
NAICS6214	Outpatient care centers
NAICS6215	Medical and diagnostic laboratories
NAICS6216	Home health care services
NAICS6221	General medical and surgical hospitals
NAICS6222	Psychiatric and substance abuse hospitals
NAICS6223	Specialty (except psychiatric and substance abuse) hospitals

This research focuses on establishments located in metropolitan areas. Scott (2006) argues that creativity and innovation manifest themselves most meaningfully at the urban and regional level. In order to identify regional effects, one needs to use a geographic region with meaningful boundaries that encompass economic activity. In the United States, such regions are the MSAs.[5] The definitions (boundaries) of metropolitan areas are constantly re-defined by the Office of Management and Budget (OMB) to reflect the current state of economic linkages in the U.S. urban areas.

Figure 5.3 depicts the dynamics of firm exit over the study period in the sectors of interest. The figure shows more active firm formation in computer and electronic manufacturing sector in 1991, followed by a higher level of exit during the first 10 years of observation. The number of firms closing business in healthcare services grows in the first 5 years and then stays at the same level of around 40–60 establishments per year.

5.6 Independent Variables and Control Group

5.6.1 Innovation

There are multiple ways to measure innovation in a region. The most common ones include R&D expenditures, share of employment in knowledge-intensive industries, and patent counts. When using patent counts as an approximation for

[5] We follow the November 2008 definition of MSAs by the U.S. Office of Management and Budget.

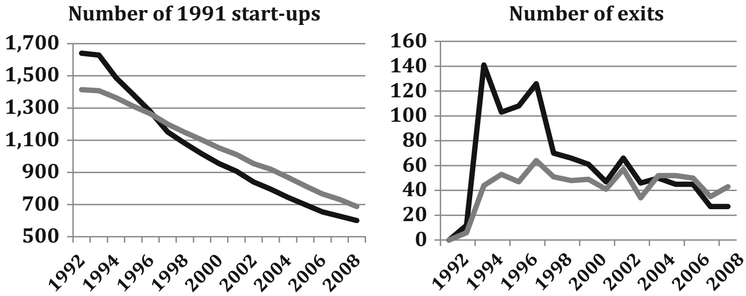

Fig. 5.3 Entry and exit dynamics in computer and electronic product manufacturing (*black line*) and healthcare services (*grey line*)

the innovativeness of a regional economy, one has to understand what exactly this statistic measures and what is does not measure. By definition, patent counts are able to account only for inventions that have been assessed and granted a patent by the U.S. Patents and Trademark Office (PTO). Innovations that go 'unnoticed' by this governmental authority, and innovations that are denied a patent, are not captured by the patent count variable. In addition, the economic value of each patent (and, thus, its usefulness) differs greatly (Griliches 1979; Pakes and Griliches 1980). Despite this fact, patent count is perhaps the best readily available indicator of underlying inventive activity in any region of an entire country (Acs et al. 2002; Feser 2002; Griliches 1990). We use the number of patents in a MSA per 1,000 residents as the variable that measures innovation in a metropolitan area.[6] The U.S. PTO is the data source.

For each of the two industrial sectors studied in this research, firms are separated into three groups depending on the average patenting activity in the metropolitan

[6] For the purposes of this study, each patent is attributed to a MSA on the basis of the inventor's reported address. If inventors listed on a patent reside in different MSAs, corresponding share is assigned to each metropolitan area. The patent year is determined by the application date. Because of the processing and reporting delay, the data for the last several years is not quite complete. To mitigate this problem, we adjust the total patent counts for the years 2006, 2007, and 2008 by 5 %, 10 %, and 15 %, respectively, using the following formula:

$$\widehat{\mathrm{Patents}}_{jt} = \mathrm{Patents}_{jt} + y\overline{\mathrm{Patents}_{j}}$$

where $\widehat{\mathrm{Patents}}_{jt}$ is the calculated total number of patents in MSA j applied for in year t. This number, standardized by population count in a given MSA, *Patents*, is used in estimation. $Patents_{jt}$ is a patent count in MSA j reported by U.S. PTO for year t. $\overline{Patents_j}$ is the average patent count in MSA j over years 1992–2005. $t \in [2006, 2008]$; $y = 0.05$ if $t = 2006$, $y = 0.1$ if $t = 2007$, $y = 0.15$ if $t = 2008$.

Table 5.2 Descriptive statistics for the firm groups based on the average level of innovation

Level of metropolitan innovation	Number of firms	Mean	Std. dev.	Minimum	Maximum
Computer and electronic product manufacturing (HTM)					
Low	545	0.20	0.08	0.03	0.31
Medium	555	0.36	0.03	0.31	0.41
High	541	1.07	0.94	0.41	3.73
Healthcare services (HTS)					
Low	466	0.12	0.05	0.01	0.22
Medium	479	0.29	0.04	0.22	0.37
High	469	0.63	0.51	0.37	3.83

area where a firm is located.[7] Establishments in the low innovative group are those with the value of average metropolitan patenting up to the 33rd percentile; establishments in the high innovative group are the ones above the 67th percentile; remaining establishments belong to the medium group. Table 5.2 presents summary statistics for innovation by group.

5.6.2 'Creative Destruction'

The 'creative destruction' regime is related to the intensity of entry in a market. In the Schumpeterian view, new entrants should impose competitive pressure on incumbents and eventually force them to exit. On the other hand, the level of entry may indicate overall conditions and opportunity for growth in a given industry. Large profit margins are likely to stimulate active firm formation. For each industrial sector, we calculate the population-adjusted number of new firms in a given year in each metropolitan area. This number is averaged over years for each firm, based on the metropolitan area they are located in, in each sectoral dataset. The observations are then divided into three groups using the 33rd and 67th percentile cutoffs. As a result, we obtain groups approximating metropolitan business environments with low, medium, and high levels of 'creative destruction'. The NETS Database and the U.S. Census Bureau are the data sources. Table 5.3 contains summary statistics for the three groups in the two datasets.

[7] Calculating average patenting for each firm, as opposed to the patenting activity for each metropolitan area, ensures that the firm stays in the same group over time. If a firm does not move to a different MSA during the study period, the value of average patenting activity for a firm should be almost identical to the average patenting activity of the metropolitan area it is located in.

Table 5.3 Descriptive statistics for the firm groups based on the average level of metropolitan 'creative destruction'

Intensity of 'creative destruction'	Number of firms	Mean	Std. dev.	Minimum	Maximum
Computer and electronic product manufacturing (HTM)					
Low	541	12.28	2.76	1.36	15.97
Medium	560	21.94	3.81	15.98	28.06
High	540	46.02	31.79	28.08	139.75
Healthcare services (HTS)					
Low	445	10.36	3.79	0.00	14.42
Medium	530	16.87	1.37	14.46	19.21
High	439	35.86	13.34	19.22	217.61

5.6.3 Business Density and Population Density

Business concentration and population density are two alternative measures of urbanization. If business tends to locate in proximity to resources, consumers, and infrastructure, high business density is likely to signal that the environment is conducive to business success. At the same time, localized economies are likely to impose competitive pressure and increase hazard rate. The survival literature reports both positive (Renski 2011; Wennberg and Lindqvist 2010) and negative (Sorenson and Audia 2000; Stuart and Sorenson 2003) effects of industrial concentration and population density on firm survival. Following the same procedure we used for the other two variables, we separate all the observations of each sectoral dataset into three groups based on the average level of metropolitan business density, and in three other groups based on the average level of metropolitan population density. The total number of firms in each metropolitan area by year is derived from the NETS Database by aggregating establishment-level data into MSA-level variables. Population estimates come from the U.S. Census Bureau. The same source is used to calculate metropolitan land area. Basic descriptive statistics for business density groups are given in Table 5.4, while Table 5.5 presents descriptive statistics for groups based on the levels of population density. Table 5.6 presents the total number of firms in each group defined by metropolitan innovation and each control variable, used in the analysis.

5.7 Equality of Survival Functions Test

We test for the equality of the survival functions for the groups of firms located in the low, medium, and highly innovative environments, first without control variables and subsequently using one control variable at a time. Table 5.7 contains the results of the Peto-Peto-Prentice test performed for all firm groups using STATA.

Table 5.4 Descriptive statistics for the firm groups based on the average level of metropolitan business density

Level of business density	Number of firms	Mean	Std. dev.	Minimum	Maximum
Computer and electronic product manufacturing (HTM)					
Low	541	31.39	14.84	1.07	56.72
Medium	558	89.63	23.20	57.45	141.06
High	542	304.07	121.82	143.00	481.76
Healthcare services (HTS)					
Low	466	21.64	10.47	1.16	42.62
Medium	483	77.66	27.01	42.73	136.72
High	465	299.39	126.34	137.16	481.76

Table 5.5 Descriptive statistics for the firm groups based on the average level of metropolitan population density

Level of business density	Number of firms	Mean	Std. dev.	Minimum	Maximum
Computer and electronic product manufacturing (HTM)					
Low	541	2,320	1,029	114	4,264
Medium	559	6,362	1,746	4,277	10,682
High	541	19,737	6,367	10,683	27,045
Healthcare services (HTS)					
Low	470	1,681	739	92	2,884
Medium	479	5,151	1,711	2,885	9,039
High	465	17,317	7,316	9,081	27,045

Table 5.6 Number of firms in bivariate groups

Control variables	Level of control variables	Computer and electronic product manufacturing (HTM), level of innovation			Healthcare services (HTS), level of innovation		
		Low	Medium	High	Low	Medium	High
Intensity of 'creative destruction'	Low	324	149	68	146	186	113
	Medium	185	226	149	93	169	268
	High	36	180	324	227	124	88
Business density	Low	325	93	123	327	66	73
	Medium	132	138	289	114	161	208
	High	88	324	129	25	252	188
Population density	Low	326	93	122	319	80	71
	Medium	186	117	255	120	178	181
	High	33	345	164	27	221	217

We first run the overall test, which compares survival functions for all three innovative groups, without controlling for other variables describing the metropolitan environment. As the top line in Table 5.7 indicates, the survival functions are statistically different between innovative groups only in the case of healthcare

Table 5.7 Peto-Peto-Prentice test results by group

		HTM, Peto-Peto-Prentice test		HTS, Peto-Peto-Prentice test	
Control variables	Level of control variables	$\chi^2(1)$	Pr > χ^2	$\chi^2(1)$	Pr > χ^2
Overall test		0.58	0.749	8.21	**0.017**
Intensity of 'creative destruction'	Low	17.05	**0.000**	0.80	0.669
	Medium	7.96	**0.019**	1.12	0.572
	High	56.96	**0.000**	11.14	**0.004**
Business density	Low	0.30	0.859	13.42	**0.001**
	Medium	5.04	0.080	9.79	0.008
	High	6.01	**0.050**	13.34	**0.001**
Population density	Low	0.94	0.626	8.03	**0.018**
	Medium	1.92	0.383	7.50	**0.024**
	High	121.02	**0.000**	1.18	0.553

Pr > χ^2 in **bold** is significant at the 0.05 level

services. Repeating the analysis separately for various levels of 'creative destruction' and urbanization reveals other significant differences. In the computer and electronic product manufacturing sector, survival functions among groups of companies located in low, medium, and highly innovative MSAs are statistically different when the level of 'creative destruction' is fixed. If urbanization level is accounted for, survival functions differ only in the highly agglomerated areas. In healthcare services, firms located in the areas with dissimilar levels of innovation enjoy statistically distinct survival functions in areas with high intensity of 'creative destruction'; low and high levels of business density; and low and medium levels of population density.

5.8 Smoothed Hazard Estimates

We continue the non-parametric analysis by plotting overall smoothed hazard estimates for firms in the three innovative groups as well as smoothed hazard estimates for the three groups keeping the levels of other three control variables fixed. Figures below display the graphs for both high-technology manufacturing and high-technology services. Each plot includes three curves that correspond to the three innovation levels of the metropolitan area firms are located in. The global hazard functions for both sectors (Fig. 5.4) reveal divergent patterns in the two sectors. In the computer and electronic product manufacturing sector, establishments in highly innovative metropolitan areas generally face higher hazard than those located in MSAs with low level of innovation on average. The opposite is true for healthcare services. In this sector, the smoothed hazard estimates are inversely J-shaped with hazard peaking at around 12 years after entry. In both cases, the hazard functions for firms in the areas characterized by medium level of

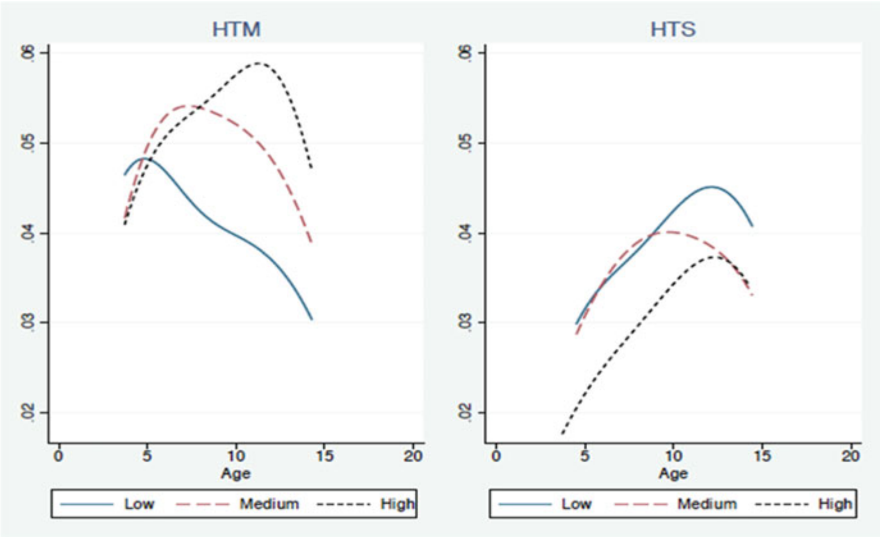

Fig. 5.4 Overall smoothed hazard estimates by innovation level of the metropolitan area firms are located in

innovation lie between the curves for low and high metropolitan innovation. Noteworthy, hazard in high-technology manufacturing is higher than hazard in high-technology services. This goes in line with the entry and exit dynamics depicted in Fig. 5.3. The results for the HTM sector, however, should be taken with caution given the inferential evidence from the Peto-Peto-Prentice test.

5.8.1 Smoothed Hazard Estimates Controlling for 'Creative Destruction'

To discern the effects of some metropolitan characteristics on hazard faced by companies in metropolitan areas with varying levels of innovation, we fix one 'control' variable at a time and compare smoothed hazard estimates for observations grouped by patenting intensity. Figure 5.5 presents results for establishments located in MSAs with low level of entry in the sectors of interest. In HTM, companies in more innovative areas face increasing hazard, while hazard faced by companies in less innovative regions decreases after the first few years. In the first 8 years, the likelihood of exit is higher in the non-innovative areas compared to the innovative one, and after 8 years this relationship reverses. Establishments in MSAs with medium level of innovation are more likely to survive longer but the probability of exit increases with time. In HTS, companies in more innovative metropolitan areas face higher hazard, which decreases over

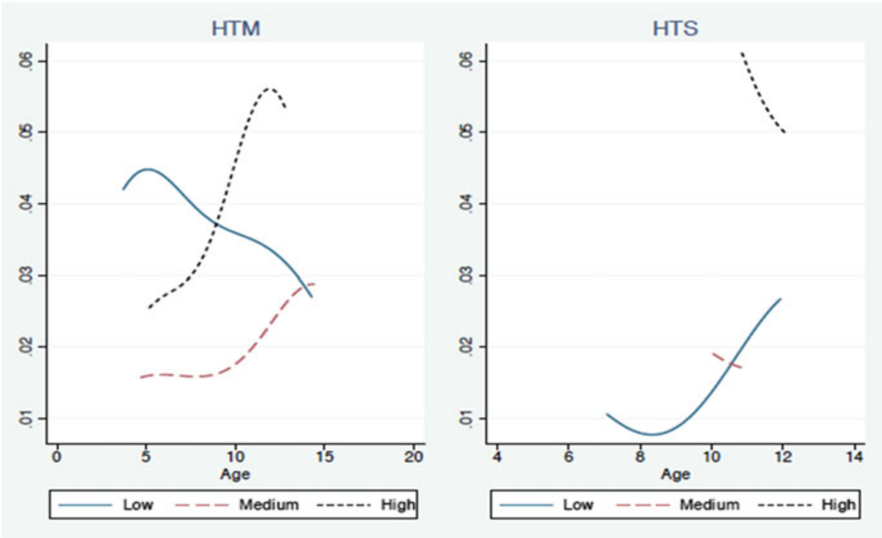

Fig. 5.5 Smoothed hazard estimates for the group of firms with a low level of 'creative destruction'

time. Establishments in non-innovative areas enjoy relatively low J-shaped hazard, although the difference is not statistically significant.

In Fig. 5.6, identical analysis is performed for medium level of entry in the HTM and HTS sectors. On average, the hazard faced by firms in the former is higher than the hazard faced by firms in the latter. In manufacturing, we observe mostly increasing hazard for companies in innovative environments and mostly decreasing hazard faced by establishments in the non-innovative environments. As a result, businesses in MSAs with the most active patenting activity enjoy greater survival likelihood up to 6 years of operation. The opposite holds true in the following years. Firms in metropolitan areas with medium level of innovation have the highest probability of exit, which steadily increases till about 11 years and then sharply decreases. In services, hazard appears to intensify for all classes of firms. Like in the previous figure, businesses in more innovative areas have the highest likelihood of exit, but the difference failed to pass the statistical significance test.

The group with high level of 'creative destruction' presents perhaps the most interesting results among the three graphs (Fig. 5.7). First of all, the difference is significant at the 95 % confidence level in both industrial sectors. Second, in both cases, companies in most innovative MSAs enjoy the highest survival chances up to about 12 years of operation. Beyond this age, firms in regions with medium innovation are the leaders in longevity. Third, in both cases businesses in less innovative metropolitan areas suffer the highest probability of exit, although it is considerably lower in healthcare services. The two cases differ in the shape of the smoothed hazard estimates. In computer and electronic product manufacturing, the hazard is J-shaped reaching its minimum at 7 years, while in healthcare services, the hazard follows inverse U-shape peaking at 13 years.

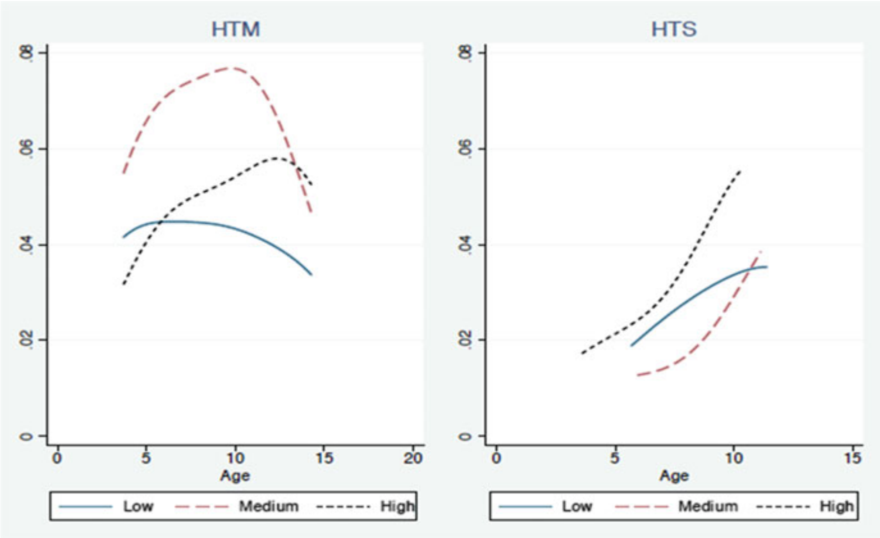

Fig. 5.6 Smoothed hazard estimates for the group with medium level of 'creative destruction'

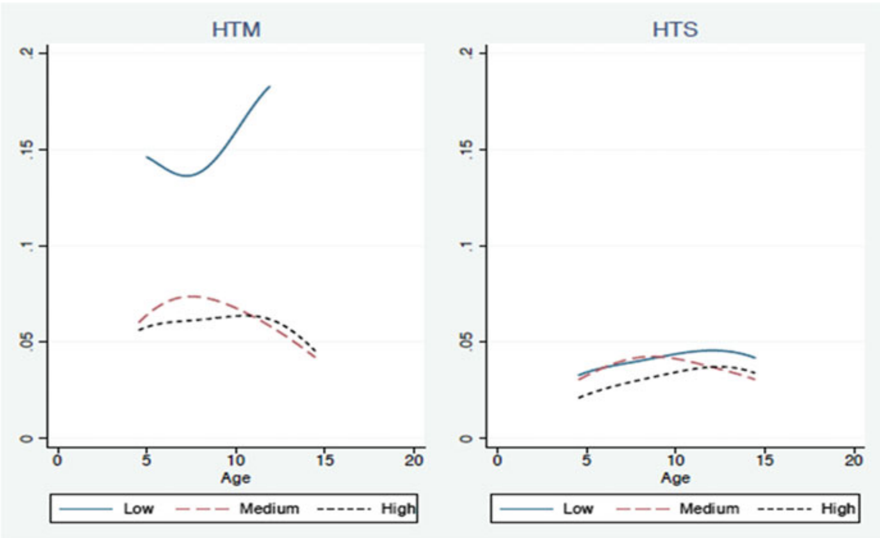

Fig. 5.7 Smoothed hazard estimates for the group with high level of 'creative destruction'

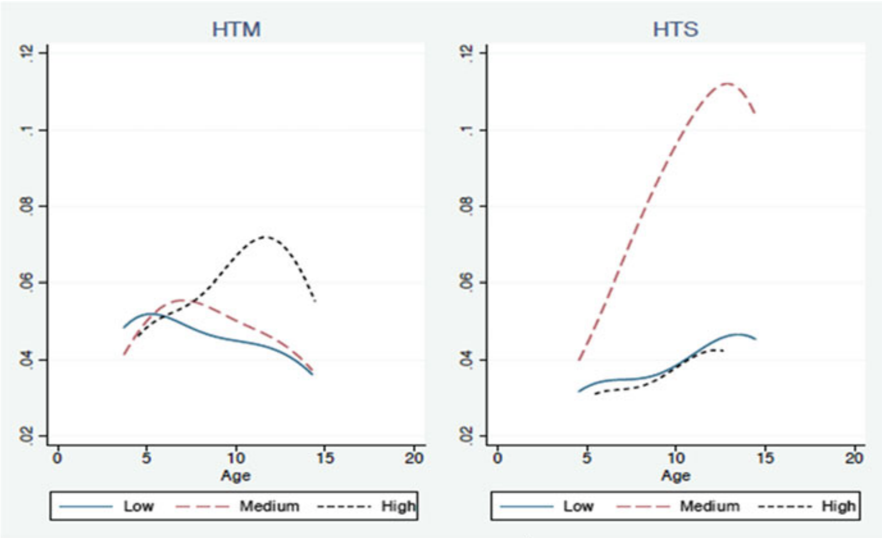

Fig. 5.8 Smoothed hazard estimates for the group of firms located in metropolitan regions with low business density

5.8.2 Smoothed Hazard Estimates Controlling for Business Density

Our next step is to control for business density, as a measure of urbanization. Figures 5.8, 5.9, and 5.10 exhibit the results for low, medium, and high level of business concentration, respectively. In Fig. 5.8, the overall relationship among low, medium, and highly innovative regions is preserved, except for the group of healthcare firms located in the areas with the medium level of the control variable. This group faces remarkably higher hazard than all other groups. The hazard level is comparable, except for the mentioned group, across HTM and HTS sectors. The differences in survival functions are statistically significant only in healthcare services.

When business density is fixed at medium values (Fig. 5.9), survival functions for the establishments in low, medium, and highly innovative groups are statistically different only at the 90 % confidence level. On average, companies in the MSAs with high patenting activity tend to exit sooner in computer and electronic product manufacturing, and to enjoy higher survival chances in healthcare services. In both sectors, the hazard faced by such businesses increases during the first decade of operation and sharply declines afterwards. In HTM, if businesses located in less agglomerated areas manage to survive till their 6-year mark, the probability of exit generally declines. In HTS, hazard faced by companies in medium- and low-innovative areas grows at least for the first 11–14 years of operation.

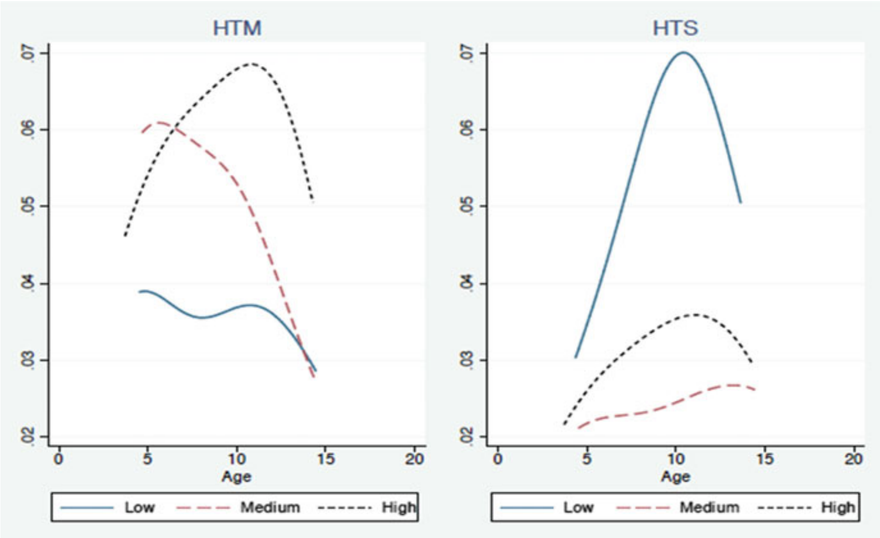

Fig. 5.9 Smoothed hazard estimates for the group of firms in metropolitan regions with medium business density

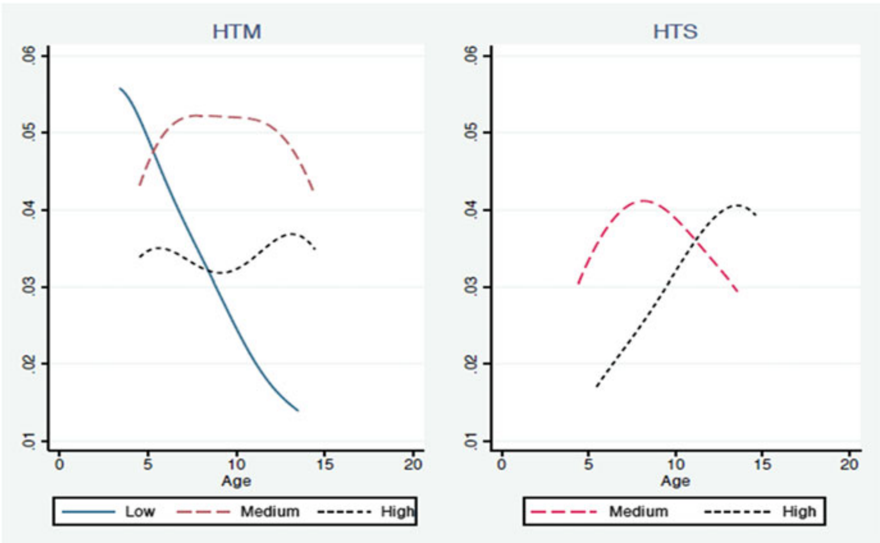

Fig. 5.10 Smoothed hazard estimates for the group of firms in metropolitan regions with high business density

For the group of metropolitan areas with high level of business concentration, smoothed hazard estimates could be produced for all subgroups except for healthcare firms in low patenting MSAs[8] (Fig. 5.10). As the figure suggests, manufacturing companies in actively patenting metropolitan areas enjoy lower hazard as compared to firms in the areas with medium level of patenting intensity. Businesses in less innovative regions have the highest likelihood of exit in the first years but the hazard gradually decreases over the study period. In healthcare services, firms in highly patenting metropolitan regions enjoy lower hazard at the beginning of the observation period. The hazard increases for the first 14 years of operation and then starts to decline. The hazard faced by companies in MSAs with medium level of innovation is inversely U-shaped, peaking at about 7–8 years. Compared to this group, firms in highly innovative regions enjoy greater likelihood of survival till their 12th year in business. After this time, the relationship reverses.

5.8.3 Smoothed Hazard Estimates Controlling for Population Density

In this subsection we describe smoothed hazard estimates for the innovative groups keeping the level of metropolitan population density constant. Figure 5.11 shows the results for the metropolitan areas with low population concentration and Fig. 5.12 for the MSAs with medium population density. In general, both graphs repeat the patterns of Figs. 5.8 and 5.9, although in the case of HTS the range of the smoothed estimated hazard is smaller.

Figure 5.13, however, demonstrates a completely different configuration. In computer and electronic product manufacturing, companies in the most innovative MSAs enjoy the lowest hazard, while those in the least innovative regions are noticeably more likely to exit. The reverse relationship is observed in the healthcare services. Estimated hazard in both sectors is much lower compared to all other groups.

Inspection of all graphs suggests the following patterns. In computer and electronic product manufacturing, the relationship between innovation and business survival is positive during the first few years. It reverses after some point in time, which depends on the level of control variables. In general, the hazard faced by companies in the more innovative group increases for about a decade and declines afterwards. This might correspond to the longest technology life cycle in this sector. If products and technologies become obsolete during this time, only those businesses that manage to come up with something new have a chance to survive past 10–12 years. All the rest are likely to go out of business. A completely different scenario is revealed for manufacturing firms in low-innovative MSAs. In almost all

8 In the MSAs with low patenting activity, only one healthcare services firm exited during the observation period. This information is insufficient to estimate and to plot hazard over time.

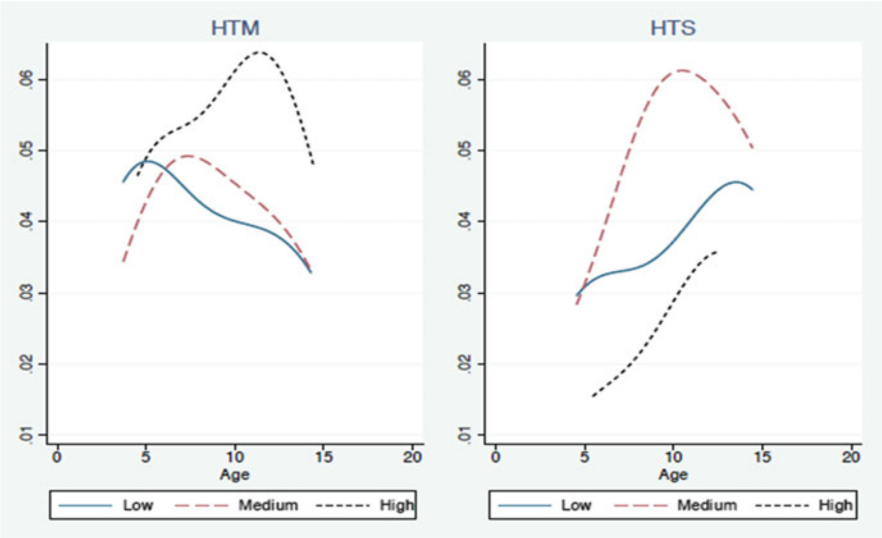

Fig. 5.11 Smoothed hazard estimates of firms in low density metropolitan regions

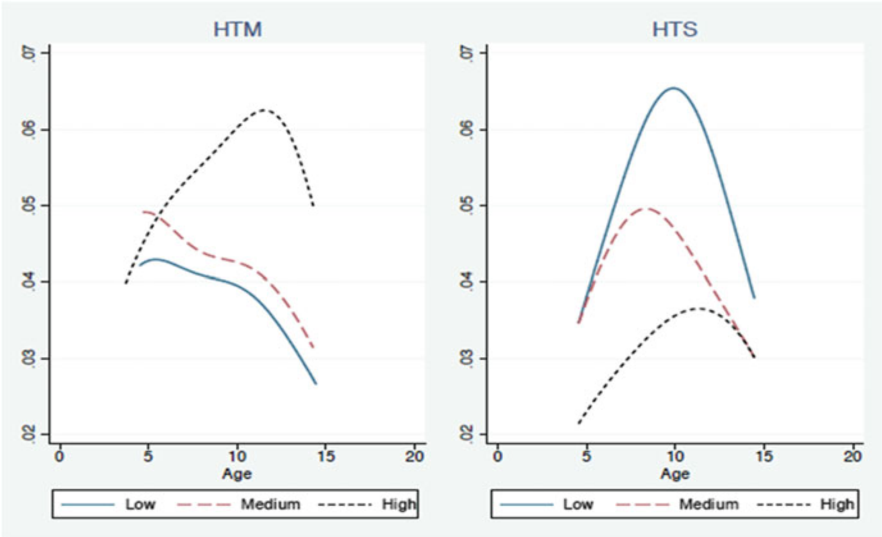

Fig. 5.12 Smoothed hazard estimates of firms in metropolitan regions with medium population density

cases considered above, the hazard estimates peak in the first 5 years and then consistently decline through the rest of the study period. The hazard functions of the group with medium level of innovation are rather unique lacking a generalizable pattern. Notably, all three graphs constructed for the high level of control variables

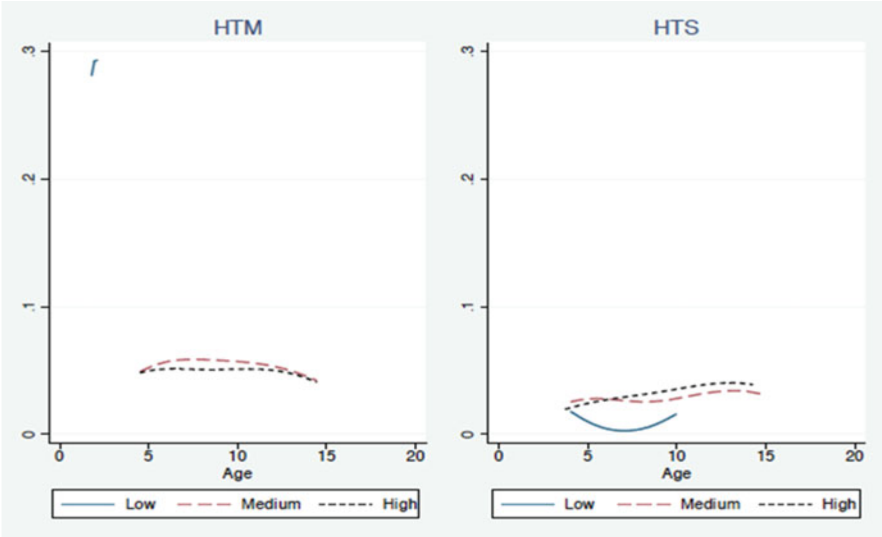

Fig. 5.13 Smoothed hazard estimates of firms in metropolitan regions with high population density

exhibit a distinct picture. In the regions with intensive entry in computer and electronic product manufacturing and dense population, the association between metropolitan innovation and business longevity is positive. In the group with highly agglomerated business activity, estimated hazard rate for companies in highly innovative MSAs remains relatively constant with minor fluctuations.

In healthcare services, the relationship between innovation in a metropolitan area and business longevity is positive, except for individual cases. This relationship reverses when the intensity of 'creative destruction' is fixed at low or medium levels, and in the group characterized by high population density. The estimated smoothed hazard functions are either generally increasing or inversely U-shaped, depending on the control variables and their levels.

5.9 Conclusions

The purpose of this chapter was to estimate the external effects of innovation, one of the major determinants of regional and business performance, on firm survival. Justification for the relationship between regional innovation and business longevity comes primarily from the agglomeration literature. It postulates that in geographic areas of business concentration, knowledge spillovers are likely to happen, which leads to increased productivity and innovativeness of all companies, even those not engaged in purposeful generation of the new knowledge. Empirical studies relate both productivity and innovativeness at a firm level to a greater likelihood of survival.

The non-parametric hazard analysis conducted in this research reveals that higher patenting intensity in a metropolitan area is associated with increased hazard in computer and electronic product manufacturing, while it appears to promote business longevity in healthcare services on average. This evidence implies diverse industrial dynamics in the sectors of interest. The change in the relationship between metropolitan innovation and business longevity from negative to positive in the densest metropolitan areas, as well as the areas with high level of HTM entry, may indicate the presence of positive knowledge spillovers or, alternatively, a self-selection process when economically more viable firms prefer to operate in more dynamic and challenging environments. At the same time, higher likelihood of exit in more innovative MSAs seems to lend some support to the Schumpeterian view of 'creative destruction'.

Further analysis of the relationship between firm survival and knowledge creation is warranted on the basis of the results of the non-parametric analysis reported here. Indeed, our current conclusions suggest that local knowledge spillovers may not have overall and universal beneficial effects on firm health. The Schumpeterian view appears to be more prevalent in one studied industrial sector than in the other, and vice versa for the Marshallian view. Also, our analysis indicates that, even for businesses in a specific industrial sector, different processes may be at play depending on the economic and business environment present in the metropolitan region. Therefore, it is our view that parametric and semi-parametric analysis should be conducted to confirm the robustness of these results with a more complete set of control variables. Also, the analysis should allow for the possibility that both the Schumpeterian hypothesis and the Marshallian hypothesis would coexist within the same metropolitan environment. In his respect, an agent-based modeling approach enabling complex and non-linear interactions among economic agents and between agents and their milieu may be quite fruitful in disentangling these seemingly contradictory relationships.

Although the present research leaves a number of specific questions unresolved, there are already very significant policy implications given that firm survival may be the best indicator of regional income and employment growth. While it is already well documented that knowledge spillovers are an important factor stimulating new firm creation, our analysis suggests that the same positive effect may not carry over to the survival of firms. Simple and undiscriminating policies that aim at encouraging knowledge spillovers, through the creating of industrial clusters for instance, may in fact hasten the death of firms, with potentially detrimental effects for local employment. The business dynamics between firm creation, firm survival, metropolitan innovation and knowledge spillovers is complex, and effective policies should recognize this diversity. For policy makers, it is important to keep in mind divergent effects the same policy may have on companies operating in different metropolitan environments, and on firms belonging to different industries. Deep knowledge of the industry in focus should help avoid inefficiency or waste of resources when designing and implementing programs aimed at specific industries or sectors.

References

Acs ZJ, Anselin L, Varga A (2002) Patents and innovation counts as measures of regional production of new knowledge. Res Policy 31:1069–1085
Acs ZJ, Armington C, Zhang T (2007) The determinants of new-firm survival across regional economies. Pap Reg Sci 86(3):367–391
Acs ZJ, Plummer L, Sutter R (2009) Penetrating the knowledge filter in “rust belt” economies. Ann Reg Sci 43(3):989–1012
Adams JD, Jaffe A (1996) Bounding the effects of R&D: an investigation using matched establishment-firm data. Rand J Econ 27(4):700–721
Agarwal R, Sarkar M, Echambadi R (2002) The conditioning effect of time on firm survival: an industry life cycle approach. Acad Manage J 45(5):971–994
Audretsch D (1995) Innovation, growth and survival. Int J Ind Organ 13:441–457
Bosma N, Stam E, Schutjens V (2011) Creative destruction and regional productivity growth: evidence from the Dutch manufacturing and services industries. Small Bus Econ 36(4): 401–418
Bottazzi L, Peri G (2003) Innovation and spillovers in regions: evidence from European patent data. Eur Econ Rev 47(4):687–710
Breschi S, Lissoni F (2001) Knowledge spillovers and local innovation systems: a critical survey. Ind Corp Change 10(4):975–1005
Brixy U, Grotz R (2007) Regional patterns and determinants of birth and survival of new firms in Western Germany. Entrep Reg Dev: Int J 19(4):293–312
Broekel T, Brenner T (2011) Regional factors and innovativeness: an empirical analysis of four German industries. Ann Reg Sci 47(1):169–194
Buss TF, Lin X (1990) Business survival in rural America: a three state study. Growth Change 21 (3):1–8
Cassia L, Colombelli A, Paleari S (2009) Firms’ growth: does the innovation system matter? Struct Change Econ Dyn 20(3):211–220
Cleves M, Gutierrez R, Gould W, Marchenko Y (2010) An introduction to survival analysis using Stata. Stata Press, College Station
Elandt-Johnson R, Johnson N (1999) Survival models and data analysis, vol 74. Wiley, New York
Fertala N (2008) The shadow of death: do regional differences matter for firm survival across native and immigrant entrepreneurs? Empirica 35:59–80
Feser EJ (2002) Tracing the sources of local external economies. Urban Stud 39(13):2485–2506
Fotopoulos G, Louri H (2000) Location and survival of new entry. Small Bus Econ 14:311–321
Fritsch M, Brixy U, Falck O (2006) The effect of industry, region, and time on new business survival – a multi-dimensional analysis. Rev Ind Organ 28:285–306
Glaeser EL, Kallal HD, Scheinkman JA, Shleifer A (2002) Growth in cities. J Polit Econ 100(1): 125–152
Globerman S, Shapiro D, Vining A (2005) Clusters and intercluster spillovers: their influence on the growth and survival of Canadian information technology firms. Ind Corp Change 14(1): 27–60
Gordon I, McCann P (2000) Industrial clusters: complexes, agglomeration and/or social networks? Urban Stud 37(3):513–532
Griliches Z (1979) Issues in assessing the contribution of R&D to productivity growth. Bell J Econ 10:92–116
Griliches Z (1990) Patent statistics as economic indicators: a survey. J Econ Lit 28(4):1661–1707
Headd B (2003) Redefining business success: distinguishing between closure and failure. Small Bus Econ 21:51–61
Henderson JV, Shalizi Z, Venables AJ (2001) Geography and development. J Econ Geogr 1(1): 81–105

Ibrahim SE, Fallah MH, Reilly RR (2009) Localized sources of knowledge and the effect of knowledge spillovers: an empirical study of inventors in the telecommunications industry. J Econ Geogr 9:405–431
Knoben J, Oerlemans LAG (2006) Proximity and inter-organizational collaboration: a literature review. Int J Manag Rev 8(2):71–89
Koo J (2005) Technology spillovers, agglomeration, and regional economic development. J Plann Lit 20:99–115
Krugman P (1991) Geography and trade. MIT Press, Cambridge
Lehto E (2007) Regional impact of research and development on productivity. Reg Stud 41(5): 623–638
Littunen H (2000) Networks and local environmental characteristics in the survival of new firms. Small Bus Econ 15:59–71
Manjon-Antolιn MC, Arauzo-Carod J-M (2008) Firm survival: methods and evidence. Empirica 35:1–24
Pakes A, Griliches Z (1980) Patents and R&D at the firm level: a first report. Econ Lett 5(4): 377–381
Porter M (1990) The competitive advantage of nations. Free Press, New York
Renski H (2009) New firm entry, survival, and growth in the United States: a comparison of urban, suburban, and rural areas. J Am Plann Assoc 75(1):60–77
Renski H (2011) External economies of localization, urbanization and industrial diversity and new firm survival. Pap Reg Sci 90(3):473–502
Rodriguez-Pose A, Comptour F (2012) Do clusters generate greater innovation and growth? An analysis of European regions. Prof Geogr 64(2):211–231
Rodriguez-Pose A, Crescenzi R (2008) Research and development, spillovers, innovation systems, and the genesis of regional growth in Europe. Reg Stud 42(1):51–67
Schmutzler A (1999) The new economic geography. J Econ Surv 13(4):355–379
Schumpeter J (1942) Capitalism, socialism and democracy. Harper and Row, New York
Scott A (2006) Entrepreneurship, innovation and industrial development: geography and the creative field revisited. Small Bus Econ 26(1):1–24
Segarra A, Callejón M (2002) New firms' survival and market turbulence: new evidence from Spain. Rev Ind Organ 20(1):1–14
Sorenson O, Audia P (2000) The social structure of entrepreneurial activity: geographic concentration of footwear production in the United States, 1940–1989. Am J Sociol 106(2):424–461
Stephan A (2011) Locational conditions and firm performance: introduction to the special issue. Ann Reg Sci 46(3):487–494
Stough R, Nijkamp P (2009) Knowledge spillovers, entrepreneurship and economic development. Ann Reg Sci 43(4):835–838
Strotmann H (2007) Entrepreneurial survival. Small Bus Econ 28(1):87–104
Stuart T, Sorenson O (2003) Geography of opportunity: spatial heterogeneity in founding rates and the performance of biotechnology firms. Res Policy 32(2):229–253
Tödtling F, Wansenböck H (2003) Regional differences in structural characteristics of start-ups. Entrep Reg Dev 15:351–370
Uyarra E (2010) What is evolutionary about 'regional systems of innovation'? Implications for regional policy. J Evol Econ 20(1):115–137
Wang Z, Ma C, Weng G, Wang Y (2004) A study on temporal and regional process of knowledge spillover. Ann Reg Sci 38(4):595–606
Wennberg K, Lindqvist G (2010) The effect of clusters on the survival and performance of new firms. Small Bus Econ 34(4):221–241
Zachariadis M (2003) R&D, innovation, and technological progress: a test of the Schumpeterian framework without scale effects. Can J Econ 36(3):566–586

Part II
Human Capital and Regional Growth

Chapter 6
The Shift-Share Regression: An Application to Regional Employment Development in Bavaria

Uwe Blien, Lutz Eigenhüller, Markus Promberger, and Norbert Schanne

6.1 Introduction

The so-called Shift-Share-Regression is used to analyse the development of employment. This does not imply a deterministic decomposition such as in classical Shift-Share-Analysis (Dunn 1960; Loveridge and Selting 1998). Instead, Shift-Share-Regression is a powerful and flexible econometric tool, which is especially suitable for testing theory-based hypotheses. In a basic version it was introduced by Patterson (1991) as a method for analysing and testing regional industrial developments. In contrary to the deterministic Shift-Share-Analysis employment development was examined in a linear model. In Patterson's analysis the industrial sector structure was used as the sole determining factor alongside the location effects and the national trend, parallel to those of the deterministic analysis. Möller and Tassinopoulos (2000) extended Patterson's approach by an additional variable for regional concentration. Further theory-based influences were then integrated in various IAB analyses (Blien and Wolf 2002). Some results of these studies are presented below, following an overview of the method.

Looking at the still widely used deterministic Shift-Share Method, the employment growth rate is disaggregated into several determinants. The so-called structural effect (also called "industry mix effect" or "proportional shift") shows how a region will develop when all its industrial sectors grow with the same rate as they do in a superordinate reference area (here: Western Germany). A location effect (also called "regional competitive effect" or "differential shift") represents the total "remainder" of development. Those who use this approach expect the splitting of employment development into components attributed to the industry structures and the regions themselves.

U. Blien (✉) • L. Eigenhüller • M. Promberger (✉) • N. Schanne
Institut fuer Arbeitsmarkt- und Berufsforschung (IAB), Regensburger Str. 104, D-90478 Nuernberg, Germany
e-mail: uwe.blien@iab.de; lutz.eigenhueller@iab.de; markus.promberger@iab.de; norbert.schanne@iab.de

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This procedure has often been criticised (Knudsen and Barff 1991), since it does not permit a model-based analysis. The detection of causal effects is at least problematic and the inclusion of additional explanatory variables is possible only in special cases needing a modification of the method (see e.g. Chiang's inclusion of the net export ratio into the method, Chiang 2012). A major problem is the nature of the method as a deterministic procedure which excludes significance tests and the estimation of the contribution of the "explained variance" in the approach.

Following Patterson's ideas instead of the deterministic approach, a regression model can be used if panel data is available, this regression approach can provide significance tests for a number of important influencing variables. In the following, we will explain this method in an overview. Additionally, an example of a regional analysis for a part of Germany shows what kind of results can be obtained from this enhanced approach. In this case, the influence of industrial sector structures, establishment size and qualification structures together with the regional determinants on employment growth are investigated. The regional units used are districts of Western Germany ("Landkreise" and "kreisfreie Städte"), especially in our context the districts of the federal State of Bavaria.

The analysis is motivated by theoretical considerations of different sources. The most important one refers to theoretical analyses of structural change. According to a theorem which can be traced back to Neisser (1942), the employment effect to technological progress depends on the elasticity of product demand. If demand is inelastic the direct labour saving effect of technological progress is dominating and the effect is negative. Then it is profitable for a firm to reduce its labour force.

If, however, demand is elastic a compensating effect dominates. In this case price decreases following higher productivity lead to an extension of product demand which (over-)compensates the direct labour saving effect. Then, it is profitable for a firm to increase the size of its labour force (for formal models of the two effects see Appelbaum and Schettkat 1999; Cingano and Schivardi 2004; Blien and Sanner 2006).

It can be assumed that in different industries of an economy different demand elasticities are dominating. Therefore, an empirical analysis of employment effects should focus on the industries of an economy. Apart from this, the locational advantages and disadvantages of the different regions can be related to (dis-)agglomeration effects discussed in important theoretical approaches following Krugman (1991) and Fujita et al. (1999) and tested in a huge amount of empirical literature (Glaeser and Gottlieb 2009; Blien et al. 2006 and many others). Therefore the two main dimensions emphasized in deterministic Shift-Share Analysis and in Shift-Share Regression are justified by important contributions. The other sets of variables included in the recent Shift-Share Regressions e.g. concerning the qualification structure are important for controlling purposes which can also be justified by a bulk of literature we will introduce later.

Investigations oriented towards the Shift-Share Regression were done within the IAB projects "Development of East German Regions" (ENDOR Project, see Blien et al. 2003, see also Blien and Suedekum 2007) and "Comparative Analysis of

German Federal State Labour Markets" (VALA)[1] see Amend and Otto (2006) for the theoretical background and Ludsteck (2006) and Schanne (2011) on the econometric model, see also Suedekum et al. (2006 for a variation). Apart from the work of the present authors and the already mentioned IAB projects, Kowalewski (2011), Farhauer and Kröll (2012) and Dauth (2013) used the Shift-Share Regression to tackle other research questions. Zierahn (2012) presents an extension that includes the effects of spatial autocorrelation.

6.2 The Method

The structural effect of the classical Shift-Share-Analysis is defined as the regional development that would be expected if all the industries in the region would grow with the rates they show in the reference area, here Western Germany. The location effect identifies the development that deviates from this expected rate, and thus signifies the local characteristics of a region. A number of local factors which are advantageous or disadvantageous to the employment trend potentially show up in the location effect.

In contrast to the classical approach, Patterson (1991) used the following equation for his analytical tool:

$$\hat{N}_{irt} = \alpha_i + \lambda_t + \kappa_r + \varepsilon_{irt} \tag{6.1}$$

Here:

$$\hat{N}_{irt} = \frac{N_{ir(t+1)} - N_{irt}}{N_{irt}}, \quad \text{the regional employment growth in sector i}$$

α_i: effect of the economic sector i
λ_t: the period effect at particular time t
κ_r: the location effect of region r
ε_{irt}: a stochastic error term

Evidently, Patterson transferred the deterministic Shift-Share approach directly into a regression model. The employment trend is decomposed into two determinants, of which one reflects the sectoral development, whereas the other corresponds to the location effect mentioned above, representing the specific development of the respective region. The advantage of this regression analysis approach is that this location effect is separated from random developments in the region which are reflected in the error term.

[1] The analyses of the federal states were published in 2006 in issues 11 and 12 of the journal "Sozialer Fortschritt" (volume 55). A special analysis was dedicated to Bavaria which could be regarded as a brief predecessor (with a shorter data base from 1993 to 2001) of the analysis presented here (Eigenhüller 2006; see also Böhme and Eigenhüller 2005).

If the estimation is carried out in the usual way as a regression with dummy variables, then the effect of a sector could only be measured in relation to another one which serves as a reference. To avoid a case of perfect multicollinearity, a fixed effect is excluded in every set referring to regions or sectors. Since the fixed effects are then measured relative to these excluded reference categories, subsequently a re-calculation not only of the effects, but also of the levels of significance is necessary, since the population mean is far more important as a reference than is any special region (Haisken-DeNew and Schmidt 1997; Möller 1995). A comparatively 'elegant' alternative is the use of identifying restrictions resorted to by Patterson (1991). This approach is called a restricted regression (Greene and Seaks 1991). The restrictions are defined in the following way:

$$\sum_{r=1}\sum_{i=1} g_{ir}\kappa_r = 0 \tag{6.2}$$

$$\sum_{r=1}\sum_{i=1} g_{ir}\alpha_i = 0 \tag{6.3}$$

Two reasons are relevant to the inclusion of weightings in the restrictions: on the one hand, exorbitant boosts in growth rates of small sectors in a region (called "shipbuilding in the midlands"-problem) are possible, resulting in outliers and heteroscedasticity problems. On the other hand, the growth rate of global parameters cannot simply be formed from the aggregation of subunits. A weighting is necessary for the correct application of the analysis, not only multiplying the restrictions but also multiplying the equation with the square root of the employment weighting Eq. (6.1):

$$g_{ir} = \sqrt{\frac{N_{ir}}{\sum_i \sum_r N_{ir}}} \tag{6.4}$$

This implies that the estimation must be carried out by means of weighted least squares. The estimating equation then reads as follows:

$$g_{ir}\hat{N}_{irt} = g_{ir}\alpha_i + g_{ir}\lambda_t + g_{ir}\kappa_r + g_{ir}\varepsilon_{irt} \tag{6.5}$$

The weights g_{ir} are set as constants calculated as means of the observation time period. Two deviations can be observed when comparing Eq. (6.5) with Patterson's (1991) estimating equation. The first consists of the fact that Patterson used linear weightings, that is, he dispensed with forming the square roots in Eq. (6.4). The second deviation consists of him not weighting the left hand side of the equation, that is, the response variable. The latter appears to be consequent and necessary within a Weighted Least Squares approach and was already applied by Möller and Tassinopoulos (2000). The use of the square root has its justification in the fact that the use of linear restrictions in a least squares estimation would lead to a disproportionate weighting of large values. Simulations showed that only an estimation with square roots as weights leads to an approximation of global growth rates through the addition of the terms in Eq. (6.5).

This basically summarizes the entire approach, and Patterson also described it equally briefly in his original publication. What is important, however, is that this approach can be expanded, as Möller and Tassinopoulos (2000) were the first to show. Their somewhat generalised empirical equation for regional development is defined as follows (for brevity and clarity we drop the weights):

$$\hat{\mathrm{N}}_{\mathrm{irt}} = \alpha_{\mathrm{i}} + \lambda_{\mathrm{t}} + \delta_{\mathrm{y}} + \kappa_{\mathrm{r}} + \mu_{\mathrm{i}}(a_{\mathrm{ir},0} - a_{\mathrm{i},0}) + \varepsilon_{\mathrm{irt}} \tag{6.6}$$

Values of $\mu_i < 0$ showed the progress of deconcentration processes (whereas δ stood for several regional types). This was an extension with which concentration processes were to be measured. In the following, the equations are expanded with variables that are considered to be important in economic theory:

$$\hat{N}_{irt} = \alpha_i + \lambda_t + \kappa_r + \sum_{j=1}^{3} \beta_j^Q Q_{jirt} + \sum_{z=1}^{3} \beta_z^B B_{zirt} + \beta^W W_{irt} + \varepsilon_{irt} \tag{6.7}$$

with:

Q_{jirt}: The proportion of qualification group j among all employees of sector i, region r and at time t

B_{zirt}: The proportion of establishments of size range z among all employees in unit irt

W_{irt}: Wage deviation from the expected wage in irt

β: Regression coefficients

With weightings, Eq. (6.7) is extended to:

$$g_{ir}\hat{N}_{irt} = g_{ir}\alpha_i + g_{ir}\lambda_t + g_{ir}\kappa_r + g_{ir}\sum_{j=1}^{3} \beta_j^Q Q_{jirt} + g_{ir}\sum_{z=1}^{3} \beta_z^B B_{zirt} + g_{ir}\beta^W W_{irt} + g_{ir}\varepsilon_{irt} \tag{6.8}$$

The model is calculated for the whole of West Germany, as in Möller and Tassinopoulos (2000), that is, it is based on 326 regions, divided into 26 sectors. The following restrictions were set for the additional variables:

$$\sum_{j=1}^{3} g_j \beta_j^Q = 0 \tag{6.9}$$

$$\sum_{z=1}^{3} g_z \beta_z^B = 0 \tag{6.10}$$

Of course the sets of restrictions Eqs. (6.2) and (6.3) were also included. The procedure applied again leads to a restricted weighted least squares estimation without an absolute term. In contrast to the unweighted estimation, there are two additional parameters to be calculated for each set of fixed effects compared to the usual strategy which leaves out dummies. Firstly, one more coefficient has to be determined, and secondly, for the restriction a Lagrange multiplicator has to be calculated.

Relative wages are estimated to include wage levels which are interpreted as deviations from expected regional wages. Therefore, wage level equations are estimated in which the exogenous variables consist of industries, proportion of men, average age, establishment size and qualification proportions. The coefficients are determined in annual estimations, i.e. not for the whole data with a panel analysis for several years. The deviations of measured wages from the calculated expectations are then used in Eq. (6.8). The purpose of this approach was to include an indication whether a region has an exceptionally high of low wage level. Since the effects found for Eq. (6.8), however, turned out of being very small and were not significant, an interpretation of the wage effects and an enhanced presentation of the procedure is not included in this text.

For the analysis an excellent data basis was available: The data from the Employment Statistics of the Federal Employment Agency, which was integrated in the Employment History Dataset developed by the Institute for Employment Research (IAB) for the time period of 1993–2008, was used for the analysis of employment developments. This was a quite extensive data base, since data were available for each year and each employment relationship liable to social security. The applied employment data consisted of volume data, that is, the average number of employees per establishment per year. To avoid distortions caused by the increase in part-time employment, working hours were aggregated to full-time equivalents to analyse the number of employees. There was no detailed information on actual working times, only a classification of employees into three groups (18 h per week, 18 h per week to full-time, and full-time). Therefore, average values of 16, 24 and 39 h per week were assumed and these working times were then converted into full-time equivalents.

6.3 Analysis of Regional Disparities in Employment Growth in Bavaria

6.3.1 On the Influence of Various Determinants on Employment Development

The basic model Eq. (6.8) was estimated as described above. Before presenting the results, a short explanation is given concerning the hypotheses about the influence of the respective variables on employment development. Then, the results for

West Germany are presented, since these form the basis for presenting and interpreting the results at the regional level for the federal state of Bavaria.

6.3.1.1 Sectoral Structure

Since certain industrial sectors are often concentrated in a region, employment growth in the region strongly depends on the development of labour demand of the respective sectors (see Longhi et al. 2005 about the consequences of sectoral diversification). Consequently, the sectoral structure is an important determinant of a region's employment trend. As we have seen in the introduction, the elasticity of demand is important for employment in the different industries. This can also be integrated in an analysis of the product cycle, as is argued in Appelbaum and Schettkat (1999) and in Blien and Sanner (2006). They show that employment growth results rather from industries which are at the beginning of their product (life) cycle, whereas sectors at the end of their product cycle exhibit decreasing employment. The reason for this is a shift in the values of demand elasticities due to the progress of product cycles. It can be assumed that these elasticities are being larger (in absolute terms) at the beginning of the cycle. Since productivity increases result in price cuts for the customers at least in competitive markets, and demand is not yet saturated at the beginning of an industry's life cycle, the markets generate an increase in demand leading to additional employment. Conversely, productivity increases followed by price cuts do hardly generate additional demand in a saturated market. Instead, higher productivity only leads to job losses.

Therefore, the dynamics of technical progress and demand for products explain the growth and decline of industries and the regions in which they are located. In general, the development of various industrial sectors in Germany evolved very differently. Whereas the proportion of employees in the service sector mostly increased due to structural change, the proportion of employees in manufacturing industries and agriculture usually decreased.

During the period analysed, service sectors mainly exhibited a positive effect in the quantitative employment trend. Table 6.1 shows the individual effects for 26 sectors[2] in West Germany. By far the strongest positive effect (coefficient) is provided by "temporary work", which experienced a boom, especially in the second half of the investigation period, even though its proportion in relation to the total number of employees was still comparatively small. Other examples of sectors with a relatively strong positive quantitative effect are business related services as well as "health and social work". The quality of work (working conditions, income, etc.) must also be considered in the "growth sectors", especially in relation to the strong

[2] The sectoral classification is based on the NACE classification (revision 1.1), with the exception of Group KA at the level of double letters, which remained almost identical to other industrial classifications (WZ93 and WZ03 in Germany). Additionally, a distinction is made between simple, scientific (or higher valued) corporate services and temporary work in the KA group, due to their heterogeneous structure.

Table 6.1 Industrial Structure – the effect of industries on employment growth and the average proportion of employees for the time period of 1993–2008 according to sectors in West Germany

	West Germany		
	Coefficient	Significance	Proportion in %
1. Agriculture and Fisheries	−0.83	**	0.83
2. Mining, Mineral Oil and Coal, Energy	−1.66	***	1.86
3. Food, Beverages and Tobacco	−1.27	***	2.78
4. Textiles and Leather	−6.06	***	1.03
5. Wood	−2.04	***	0.70
6. Paper, Publishing	−1.62	***	2.25
7. Chemicals and Plastics	0.02		4.00
8. Glass, Ceramics, Mineral Products	−2.30	***	1.06
9. Metal Goods and Metal Processing	−0.01		4.91
10. Mechanical Engineering	0.16		4.85
11. Electrical Engineering	−0.35	**	4.73
12. Motor Vehicle Construction	1.72	***	4.01
13. Other Processing Industries, including Recycling	−2.14	***	1.21
14. Building Industry	−3.81	***	7.03
15. Trade and Repair	−0.95	***	15.12
16. Hotel and Restaurant Industry	−0.82	***	2.33
17. Transport and Telecommunications	1.05	***	5.44
18. Finance Industry	0.05		4.28
19. Simple Business-Related Services	3.16	***	2.47
20. Knowledge-intensive Business-Related Services	2.47	***	6.47
21. Temporary Work	14.30	***	1.24
22. Social Security, State, Extraterritorial Bodies	−0.59	***	5.79
23. Education and Training	0.49	*	2.38
24. Health and Social Work	1.63	***	9.32
25. Other Service Activities	0.15		3.77
26. Private Households	−1.99	**	0.14

Source: Statistics of the Federal Employment Agency and IAB Employment History; own calculations
Significance level: *95 %, **99 %, ***99.9 %

positive effect of temporary work, since this quality determines the living standard in the broader sense and influences the opportunities for social participation in society.

A predominantly negative effect is calculated for manufacturing, especially in the "Textiles and Leather" sector. The "Wood" and "Glass, Ceramics and Mineral Products" industries also show a significant negative effect. The only manufacturing industry to exhibit a significant positive effect on employment trend is "Motor Vehicle Construction".

In the following, a summarised sectoral effect for the districts is calculated and shown in Table 6.8 in the Annex. This sectoral effect then displays the extent to which employment growth in the districts deviates from the average West German employment growth, because the industrial mix differs from the West German industrial mix. A positive (negative) sectoral effect is given when industries

Table 6.2 Establishment size structure: the effect of establishment size on employment growth ("coefficient") and the average proportion of employees in the time period 1992–2008 according to establishment size in West Germany

	West Germany		
	Coefficient	Significance	Proportion in %
Smaller establishments (up to 50 employees)	1.28	***	36.19
Medium establishments (51–250 employees)	0.39	*	25.98
Larger establishments (more than 250 employees)	−1.49	***	37.83

Source: Statistics of the Federal Employment Agency and IAB Employment History; own calculations
Significance level: *95 %, **99 %, ***99.9 %

exerting a positive (negative) effect on employment growth are disproportionately represented in a region. In the same way the other basic components of the model are treated.

6.3.1.2 Establishment Size Structure

In the following we discuss establishments as the local production units of a firm. A growing significance of small to medium-size establishments can be observed in Western industrial nations in recent decades. Various developments have contributed to this. Technological change has lead to a significant decrease in costs of transport and communications, and at the same time, the pressure of international competition has grown, exerting considerable adjustment pressures on establishments due to rapidly changing demand. Larger establishments reacted by introducing new, lean and more flexible organisational and management structures, for instance. Also special production and processing techniques such as just-in- time systems are used. Additionally, many establishments have outsourced services, leading to a more decentralised production structure favouring small and medium-sized units. This flexible specialisation enables rapid response to changing demand and specific customer requirements, so that these small and medium establishments can react more adequately to the general changes mentioned above. The increase in business start-ups and the expansion of employment in the service sector with many small establishments could also explain the growing significance of smaller establishments (cf. Amend and Otto 2006 for more extensive explanations and literature).

The establishments were divided into three categories of size for the quantitative analysis: smaller establishments (up to 50 employees), medium size establishments (51–250 employees) and larger establishments (more than 250 employees).

The results of the regression analysis for West Germany correspond to expectations to the extent that they exhibit a significant positive effect of small and medium-size establishments, as well as a significant negative effect for larger establishments with respect to employment trends (Table 6.2). The effect of establishment size for a region indicates the extent to which regional increase in employment deviates from the average West German increase in employment when the company size structure in the respective district or city deviates from the average West German company size structure.

6.3.1.3 Qualification Structure

As in many other countries, a shift in labour demand towards a relatively high qualified work force can also be seen in Germany. The so-called "Skill Biased Technological Change" provides an explanatory approach, according to which technical progress towards increasingly complex technologies in production and procedures leads to an increased demand for a (highly) qualified work force (cf. Acemoglu 2002). Increasing international trade is also seen as a cause of the trend to a highly qualified work force in developed countries. This consideration is also based on the fact that trade intensification promotes product specialisation, whereby industrialised countries mainly produce products requiring highly qualified workers while other countries produce products with low-skilled workers. Newer approaches also consider that technical progress not only leads to a loss or relocation of low-skilled jobs – especially in manufacturing industries – but also affects routine activities of medium-qualified employees (see Autor et al. 2003).

Therefore, the availability of qualified labour can be seen as an important factor in regional development (cf. Badinger and Tondl 2005, see also contributions in Acs et al. 2002), which is the reason why qualification structure has been included as an additional variable in the regression equation. A differentiation is made between low-skilled (without completed vocational training), medium-skilled (completed apprenticeship, technical college degree, foreman or technician) and highly-skilled (university or polytechnic degree). In addition, those without specified qualification in the employment statistics are also considered. A result of the calculation is that there is a strong positive effect for those classified as "highly qualified" and a positive effect is also found for those with unknown qualification, as well as a significant negative effect for low-skilled employees and those with a completed apprenticeship (Table 6.3). The results for the low-skilled and the highly qualified certainly agree with expectations. At first sight, the significant negative effect for the medium- skilled is a surprise. However, the effect is relatively small in comparison to the effects for other qualification groups and can be partially explained by the loss of routine jobs for this qualification level. Another possibility is that the effect might be due to polarization tendencies in the economy. The effect for those with unknown qualification is difficult to interpret.[3]

[3] The positive effect may indicate that not only low-skilled employees are in this category, but also persons from all qualification levels, including highly qualified. This assumption is confirmed by analyses that examine the occupations of those whose "qualifications are unknown". This not only includes unskilled labour.

Table 6.3 Qualification structure – effect of the qualification structure on employment growth ("coefficient") and the average proportion of employees for the period 1993–2008 in West Germany

	West Germany		
	Coefficient	Significance	Proportion in %
Without completed apprenticeship	−2.18	***	14.47
Completed apprenticeship	−0.34	**	66.81
Highly qualified (polytechnic or university degree)	3.82	***	8.45
Qualification unknown	2.16	***	10.27

Source: Statistics of the Federal Employment Agency and IAB Employment History; own calculations
Significance level: *95 %, **99 %, ***99.9 %

It should be mentioned that the occurrence of skill-biased technological change does not exclude the existence of (partial) over-qualification in the economy, since the labour market is segmented. Higher demand for high-qualified people might not improve the situation of many workers who are over-qualified for their specific jobs. In the German economy segments according to occupations are of special importance.

6.3.1.4 Local Conditions

The location effect encompasses a systematic influence of the respective region which cannot be explained by other variables. This covers a constellation of specific regional conditions. This can, for example, be an especially favourable combination of industrial sectors in the region which leads to the regional economy benefiting from spill-over effects. Another example concerns special qualifications of employees which are not represented in the categories of formal education included in the regressions. Also population development, the question whether we are dealing with an immigration or emigration region has to be considered within the context of the location determinant.

Other local factors concern the geographical location of regions. This can be the proximity to large sales markets or procurement markets, available infrastructure, the accessibility of a region and the availability of research and development institutions. The geographical situation and natural environment of a region, the opening of a border, the closure or establishment of important establishments in the region can also play a role. Additionally, special economic or labour market measures and "soft" location factors such as quality of life or the reputation of a region with respect to being business-friendly are also important.

6.3.2 Employment Developments and Influences of the Determinants in the Bavarian Districts

In the period of 1993–2008, the federal state of Bavaria exhibited an average annual employment growth of 0.01 %. Conversely, all other West German federal states experienced a decrease in employment. A previous version of the following analysis was included in a report in German language (Blien et al. 2011).

However, the calculations also exhibit large differences between the Bavarian districts (see Map 6.1[4]). Nevertheless, a positive effect was registered for the majority of the regions between 1993 and 2008. A more or less distinct increase in employment occurred in 54 of the 96 districts. A table with the values of increase in employment of all the districts as well as the individual determinants is given in the Annex of this chapter (Table 6.8). Employment in the district of Erlangen-Höchstadt and Freising increased to the largest extent – by an annual average of more than 2 %. These are also the two largest growth rates in West German comparison. In some of these districts the level of full employment (for a discussion of the term see Promberger 2012) is reached. In almost all parts of Bavaria there are districts with an increase in employment. At the same time, there are also regions where employment has developed unfavourably. The most severely affected region was North Eastern Bavaria. There, the most significant employment loss occurred in the district of Wunsiedel in the Fichtelgebirge, where employment dropped by an annual average of almost 2 %.

There is a gap in the employment development between South and North Bavaria for the years 1993–2008. On the one hand, comparatively many regions in Northeastern Bavaria experienced the greatest employment losses, and on the other hand, seven of the ten districts with the strongest employment increases were located in South Bavaria.

No overall distinction can be found for the employment trend between cities and rural areas. It can be seen, however, that Munich is working as a powerful "economic machine", which gives rise to many employment relationships not only in this city, but in the whole area of Southern Bavaria. There may be spill-overs from this centre which may reach as far as the commuting area of Munich extends. This area includes the southern part of Bavaria completely. On the other hand, in the city of Munich also some signs of "over-agglomeration" are visible. Some of the districts with the best employment development can be found in the surrounding area. These districts may profit from agglomeration disadvantages of the city, such as high real estate prices and rents. Therefore, some firms may prefer locations outside the centre of the agglomeration.

The situation in the Nuremberg agglomeration in Northern Bavaria is not as favourably. Nuremberg is smaller and has some problems with a partly obsolete industry structure. This city cannot generate as many positive spill-overs as Munich

[4] In forming the class categories, the starting point was the mean value for all West German districts, and a half and one standard deviation was added or subtracted to each.

does. The urban units of Nuremberg, Fürth and Schwabach, and also the adjacent districts of Fürth and Nuremberg Land show bad figures of employment development. The positive influence of the smaller Nuremberg agglomeration on other regions is limited in comparison to the Munich agglomeration. On the other hand, there are also some districts with a pronounced favourable development e.g. in Erlangen and especially in the district of Erlangen-Höchstadt.

Following this overview of employment growth in the Bavarian regions, the next section will depict the influence of the already introduced variables of industrial structure, establishment size, qualification structure and location factors have on the various employment development.

6.3.2.1 The Sectoral Effect in Bavarian Regions

The influence of the sectoral structure for employment growth in Bavaria turns out to be slightly negative (0.08 percentage points), whereby the differences in the sectoral structure concerning employment between Bavaria and West Germany are generally slight (cf. Table 6.4). The negative effect of the mix of trades and industry can be attributed to the fact that employment shares are above average in many sectors of the manufacturing sector and that these sectors are linked to substandard employment trends. The difference between Bavaria and West Germany is most distinctive in the "electrical engineering sector", as the share of 6.8 % in Bavaria is 2 percentage points higher than in West Germany. In addition, the service sectors, which have a positive effect on employment trends, tend to be under-represented in Bavaria.

The "Health and Social Sector", the "Scientific Corporate Services", or the "Simple Business-Related Services", for example, are strongly under-represented in Bavaria. "Temporary Work", the sector with the highest positive coefficient, reveals a smaller share in employment than West Germany, but only by 0.04 percentage points. This deficit in the service sector and the employment shares that are above average in other sectors of the processing industry cannot be compensated with the more positive effect of a comparatively high share of employment in "Motor Vehicle Construction".

Concerning the effects of the sectoral determinants on employment growth, there is a distinct difference between cities and rural districts (see Map 6.2). Cities mostly have a positive sectoral composition effect. The influence is strongest for Ingolstadt (+1.12 percentage points), Regensburg (+0.65 percentage points), and Munich (+0.55 percentage points). These positive results for cities can be primarily attributed to the fact that the service sector is over-represented. Examples of this are Munich and Nuremberg with significantly above average values for "Knowledge-intensive Business-Related Services" (12.4 % or 10.4 %). There is a distinctive "Financial Sector" with an employment share of slightly more than 16 % in Coburg, and 16.4 % and 15.1 % of the employees in Würzburg and Straubing are in "Health and Social Work". Temporary work also plays a role in some cities.

Bavaria gains much from the car production. Just under 45 % of the employees in Ingolstadt work in the industry of "Motor Vehicle Construction", and in Regensburg the figure is 10.6 %. Three other districts, Freising, Starnberg and

Table 6.4 Industrial structure – the average share of employees according to industry for the period 1993–2008 in Bavaria and the difference from West Germany

	Bavaria	
	Share in %	Difference from West Germany
1. Agriculture and Fisheries	0.72	−0.11
2. Mining, Mineral Oil and Coal, Energy	1.44	−0.43
3. Food, Beverages and Tobacco	3.22	0.45
4. Textiles and Leather	1.41	0.37
5. Wood	0.89	0.19
6. Paper, Publishing	2.41	0.17
7. Chemicals and Plastics	3.39	−0.62
8. Glass, Ceramics, Mineral Products	1.64	0.58
9. Metal Goods and Metal Processing	3.23	−1.68
10. Mechanical Engineering	5.27	0.42
11. Electrical Engineering	6.76	2.03
12. Motor Vehicle Construction	4.48	0.47
13. Other Processing Industries, including Recycling	1.47	0.26
14. Building Industry	7.47	0.44
15. Trade and Repair	14.53	−0.60
16. Hotel and Restaurant Industry	2.84	0.51
17. Transport and Telecommunications	4.76	−0.68
18. Finance Industry	4.33	0.05
19. Simple Business-RelatedServices	2.32	−0.15
20. Knowledge-intensive Business-Related Services	6.10	−0.37
21. Temporary Work	1.20	−0.04
22. Social Security, State, Extraterritorial Bodies	5.31	−0.48
23. Education and Training	2.27	−0.11
24. Health and Social Work	8.91	−0.40
25. Other Service Activities	3.45	−0.33
26. Private Households	0.18	0.04

Source: Statistics of the Federal Employment Agency and IAB Employment History; own calculations

Munich, show a positive influence of the sectoral effect, favoured by their proximity to the capital, since there is a high proportion of “Knowledge-intensive Business-Related Services” in Munich and in Starnberg (16.4 % and 12.1 %), and the very large significance of the “Transport and Communications” sector with an employment share of 26.1 % in Freising, the location of the Munich Airport.

Some North-eastern Bavarian districts are particularly affected by a bad industrial structure. The unfavourable development in this part of the country is at least partly explained by an outdated industry structure.

6.3.2.2 The Establishment Size Effect in the Bavarian Regions

The establishment structure in Bavaria hardly differs from the structure in West Germany and a minimal positive effect of +0.01 percentage points can be calculated

Table 6.5 Structure of establishment size: average proportion of employees by classes of establishment size for the period 1993–2008 in Bavaria, and the difference from West Germany

	Bavaria	
	Proportion in %	Difference from West Germany
Smaller establishments (up to 50 employees)	37.01	0.82
Medium-sized establishments (51–250 employees)	25.08	−0.90
Larger establishments (more than 250 employees)	37.91	0.08

Source: Statistics of the Federal Employment Agency and IAB Employment History; own calculations

for Bavaria in relation to Western Germany. Bavaria profits from a proportion of employees in smaller establishments that is above average, with a positive effect on the employment trend. This proportion compensates the smaller proportion of employees in medium-sized establishments and the slightly above average proportion of employees in large establishments with its negative effect on employment growth (see Table 6.5).

Concerning the influence of establishment size structure, there mainly is a difference between urban and rural regions (see Map 6.3). A generally positive effect is calculated for rural regions, since the proportion of small and medium-sized establishments is above average. In contrast, a negative effect is typically found for cities, because the share of employees in larger establishments is above average. Comparatively many people were employed in larger establishments in the cities, even though a suburbanisation of employment by relocation of establishments or subdivisions of establishments to the surroundings took place during the observation period. The city of Erlangen, with −0.65 percentage points, is most strongly affected by the negative influence of an above average share of employees in larger establishments, followed by the cities of Ingolstadt (−0.61 percentage points) and Schweinfurt (−0.53 percentage points). Erlangen has 64.5 % and Ingolstadt has 62.9 % of employees in large establishments, and in Schweinfurt there are 58.9 %.

6.3.2.3 The Qualification Effect in the Bavarian Regions

The qualification structure of the employees has a very slight negative influence (−0.02 percentage points) on the employment trend in Bavaria. On the whole, the negative effect on employment growth resulting from the share of employees both without professional qualifications and with a medium qualification level being above average is almost compensated by the positive effect of the share of employees with a university education which is also above average (see Table 6.6).

The distribution of the qualification effects (cf. Map 6.4) also shows the difference between cities and rural districts, and mirrors the functional division of labour between cities and rural areas to a certain extent. Management, administration and research divisions of establishments or universities (and universities of applied science) which employ a large amount of highly qualified personnel are often

Table 6.6 Qualification structure – average share of employees according to qualification level for the period 1993–2008 in Bavaria and the difference from West Germany

	Bavaria	
	Share in %	Difference from West Germany
Without completed apprenticeship or professional training	14.83	0.36
Completed apprenticeship or professional training	67.40	0.59
Highly qualified (technical university or university degree)	8.71	0.27
Qualification unknown	9.05	−1.22

Source: Statistics of the Federal Employment Agency and IAB Employment History; own calculations

found in cities or surrounding areas because of the agglomeration economies, whereas manufacturing establishments with medium-qualified or even low-skilled employment are often located outside the cities.

Overall, there are only 11 districts in Bavaria with a positive or non-negative qualification effect. Six of these regions lie within the Munich agglomeration, and the rural district of Munich has the highest positive qualification effect (+0.7 percentage points). Erlangen follows in second place (+0.67 percentage points), the city of Munich, with +0.54 percentage points is in third place.[5] This is due to the high proportion of highly qualified employees that is above average – the proportion is almost 25 % in Erlangen, 18.5 % in the city of Munich – and due to the relatively high proportion of employees of unknown qualification.

In general, shares of highly qualified employees that are below average as well as shares of employees without a completed professional training that are above average are decisive for the negative effect of the qualification structure. Comparatively strong negative qualification effects are to be found in peripheral regions of Northern and Eastern Bavaria.

6.3.2.4 The Location Effect in the Bavarian Regions

In the analysis of the growth rate as performed in the Shift-Share-Regression, the location remains as an important determinant. The location effect comprises all factors that are not included in other determinants, i.e. the sectoral determinant, qualification structures, etc., and concern the respective location relatively constantly over time. These factors include spatial conditions, local politics and coincidence. A separation of these individual sub-determinants is not possible with the available database.

Evidently, the overall location effect for the Federal State of Bavaria is relatively large and positive, with a value of +0.46 %. This is the highest value of all West

[5] Buch et al. (2010) demonstrate, for example, that Munich shows the most positive migration balance for highly qualified employees among large German cities with more than 500,000 inhabitants. The migration balance for this qualification group is also positive for Nuremberg, but to a much smaller degree than for Munich.

Table 6.7 Districts of Bavaria according to their area types and their effects on employment growth

	Bavaria		
	Number of districts in this type	Effect	Significance
Regions with large agglomerations			
Districts with core cities	4	−0.65	***
Highly urbanised districts	3	−0.02	
Urbanised districts	8	0.29	**
Rural districts	2	0.42	
Regions with conurbational features			
Districts with central cities	4	−0.26	**
Urbanised districts	14	0.50	***
Rural districts	14	0.71	***
Regions of rural character			
Urbanised districts	34	0.59	***
Rural districts	13	0.26	

Source: BBSR, Statistics of the Federal Employment Agency and IAB Employment History; own calculations
Significance level: *95 %, **99 %, ***99.9 %

German Federal States. Apart from Bavaria, only Baden-Württemberg (+0.25 percentage points) and Rhineland-Palatinate (+0.19 percentage points) exhibit positive values for the location determinant.

Many of the aforementioned factors behind the location determinant provide explanations for the situation in Bavaria. Even comparatively better figures for Bavaria in relation to some “soft” location factors could be possible. For example, the quality of life within an area could be determined as positive and be significant for the establishment and for the choice of workplace and residence among employees. According to figures from the tourist sector, Bavaria’s attractiveness is relatively high.

In addition, the settlement structure of Bavaria exerts a positive influence, due to its relatively large number of rural districts which have a more or less positive employment effect. Only eight Bavarian cities conform to the two city types in terms of area types as outlined by the German Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR), for which the analysis yields a negative effect for employment (see Table 6.7).

The overall results show a positive effect for the location determinant of the Bavarian regions (see Map 6.5). In comparison to West Germany, a positive effect is obtained for more than three quarters of the Bavarian districts, which turns out to be relatively strong in some cases when compared to the other determinants. There also tends to be a structural difference between cities and other districts for the location determinant as can be seen from Table 6.7. Large cities show a negative location effect. Seven cities, including Munich (−0.64 percentage points) and the cities of the Nuremberg agglomeration (Nuremberg: −0.73 percentage points; Fürth: −0.57 percentage points; Schwabach: −0.39 percentage points) are among the ten regions with the largest negative figures. An exception is the city of Erlangen (+0.58 percentage points). Additionally, there are some districts in

North and East Bavaria with a comparatively strong negative locational effect, and interestingly, also in Upper Bavaria. It is very remarkable, that the employment development in cities is worse than the one of other types of districts. Cingano and Schivardi (2004) discuss the possibility that the rates of technological progress are often higher in cities than elsewhere whereas the employment trend in agglomerations is often negative. This can be due to the labour saving effect of technological progress under the conditions of inelastic product demand as mentioned in the introduction of this chapter.

Since the location determinant always contains specific regional factors, a discussion of possible explanations cannot be given here for the 96 Bavarian districts. An initial point for interpreting the location determinants is in part offered by the factors mentioned for West Germany, among others, the advantages and disadvantages in agglomeration areas, population developments or migratory effects or the geographical position.

6.3.3 Discussion

The results of our analysis show that notable regional disparities exist with respect to employment development in Bavaria. This is due to the variation in the strength and direction of the influences of the various determinants on employment growth. The disparities have a structure on a large scale, since there is a North–south divide, with the North as the disadvantaged part. However, this does not entail that the entire Northern and Eastern Bavaria experienced an unfavourable employment trend or shows completely unfavourable constellations with respect to the determinants. On a small scale there are also important disparities. This is partly due to the industries located there and also partly due to the vibrancy effect of the capital, Munich, and its radiance extended recently. In contrast to this, the vibrancy effect of the agglomeration of Nuremberg, with its rather old industrial structure and also significantly smaller agglomeration is much weaker. This contributes to the fact that North Eastern Bavaria has the greatest problems of all Bavarian regions.

Bavaria benefited from a comparatively diverse and strongly export-oriented sectoral mix. This structure should also be of advantage in the future. At the same time, the very dynamic sector of corporate services could supply future potential, since the strong industrial base provides a favourable environment. In addition, there is the sector of Health and Social Work as well as Education and Training. Of course, the areas of scientific services in these sectors that require (highly) qualified personnel are especially promising for the future. It would be of advantage to reinforce these services in rural areas.

Nevertheless, the regions characterised by a rather old, traditional mix of industries should not be neglected. Even there, certain internationally well positioned subsectors and companies can be found. Therefore, such subsectors can also contribute to surviving painful readjustment processes and opening up prospects for the region, if they are supported by investment in qualified personnel and infrastructure. It is imperative for the regions to establish a promising industrial mix.

The analysis also shows that the location effect is significant for regional development. Correspondingly, it can also represent an important starting point for exerting an influence. For this, the regional competitive factors should be determined and their effects identified. This will provide possibilities to link differentiated local promotional concepts that will reinforce existing positive competitive factors or impede constellations or conditions that have negative effects. A comparative perspective can provide important new insights. This requires patience and the readiness for continuous efforts, since this is the only way to influence (path-dependent) local conditions.

6.4 Conclusion

This chapter has the objective, on the one hand, of presenting the Shift-Share-Regression method, and on the other hand, of showing how the application of this method can lead to theoretically and empirically substantial conclusions. The presentation demonstrates that this double objective can be met: a powerful "work-horse" is available in the form of the Shift-Share-Regression which is useful for many analytical assignments, and is especially suitable for regional labour market research. The example presented here for the German Federal State of Bavaria shows that numerous significant conclusions can be reached. An enormous amount of effects is revealed in the analytical results which can be related not only to theories of economic science but also implies relevant findings for economic policies. For social sciences, the analysis contributes to the explanation of employment and therefore to the distribution of social chances and (indirectly) to the emergence of poverty. Employment trends explain differences in unemployment levels, which are directly related.

We should not neglect that further extensions of the methodology could be useful for several reasons. One of these approaches has been done in the work of Zierahn (2012): this deals with the incorporation of methods of spatial econometrics. Other extensions could deal with problems of endogeneity, which, for example, could be related to the further inclusion of wage information. The Shift-Share-Regression is open to a further development in the direction of causal analysis.

Tests have shown that the Shift-Share-Regression permits much more detailed conclusions than is possible by considering regions as panels without sectoral differentiation. Of course, this is due to the fact that the differentiation according to sectors introduces a source of variation in the data which can be profitably analysed. In addition, sector differentiation is not only methodologically valuable, but also constitutes an economically and theoretically sensible classification which enables the analysis of relatively homogeneous units of observation. Due to these reasons, the use of Shift-Share-Regression is recommended for further analyses.

This is the contribution of the work which started from Patterson's seminal paper: Shift-Share-Regression is not only a method to replicate the decomposition task of deterministic approaches in a linear model. Rather, it is a flexible econometric tool, which can integrate many theoretically meaningful variables.

Annex

Table 6.8 Employment trend for the period 1993–2008 (average annual growth rate in %) and the influence of various determinants in Bavarian districts ("Landkreise" are termed "Distr" and "kreisfreie Städte". i.e. urban areas are termed "City")

	Employment growth rate	Sectoral effect	Establishment size effect	Qualification effect	Location effect
Bavaria	0.01	−0.08	0.01	−0.02	0.46
Upper Bavaria					
Ingolstadt, City	1.18	1.12	−0.61	−0.08	1.07
Munich, Federal State Capital	−0.31	0.55	−0.40	0.54	−0.64
Rosenheim, City	−0.38	−0.08	0.08	−0.04	−0.04
Altötting, Distr	−0.21	−0.11	−0.19	−0.19	0.62
Berchtesgadener Land, Distr	−0.90	−0.41	0.66	−0.08	−0.71
Bad Tölz-Wolfratshausen, Distr	−0.23	−0.25	0.59	−0.03	−0.15
Dachau, Distr	1.16	−0.27	0.48	−0.03	1.32
Ebersberg, Distr	1.31	−0.29	0.34	0.11	1.47
Eichstätt, Distr	1.86	−0.66	0.47	−0.19	2.59
EDistring, Distr	0.89	−0.37	0.43	−0.10	1.28
Freising, Distr	2.03	0.20	−0.18	0.07	2.22
Fürstenfeldbruck, Distr	−0.13	−0.46	0.64	0.14	−0.08
Garmisch-Partenkirchen, Distr	−1.44	−0.29	0.62	−0.14	−1.28
Landsberg am Lech, Distr	0.95	−0.24	0.32	−0.20	1.39
Miesbach, Distr	0.09	−0.41	0.60	−0.04	0.22
Mühldorf a.Inn, Distr	−0.22	−0.50	0.39	−0.30	0.55
Munich, Distr	1.84	0.11	0.01	0.70	1.24
Neuburg-Schrobenhausen, Distr	0.14	−0.95	0.18	−0.32	1.58
Pfaffenhofen a.d.Ilm, Distr	1.01	−0.41	0.32	−0.18	1.62
Rosenheim, Distr	0.43	−0.43	0.47	−0.15	0.87
Starnberg, Distr	0.80	0.15	0.33	0.42	0.21
Traunstein, Distr	0.01	−0.43	0.21	−0.16	0.74
Weilheim-Schongau, Distr	0.39	−0.28	0.17	−0.13	0.98
Lower Bavaria					
Landshut, City	−0.25	0.46	−0.07	−0.20	−0.07
Passau, City	0.05	−0.16	−0.08	−0.13	0.77
Straubing, City	0.67	0.21	0.18	−0.21	0.77
Deggendorf, Distr	0.22	−0.61	0.19	−0.29	1.28
Freyung-Grafenau, Distr	−0.83	−0.80	0.39	−0.58	0.53

(continued)

Table 6.8 (continued)

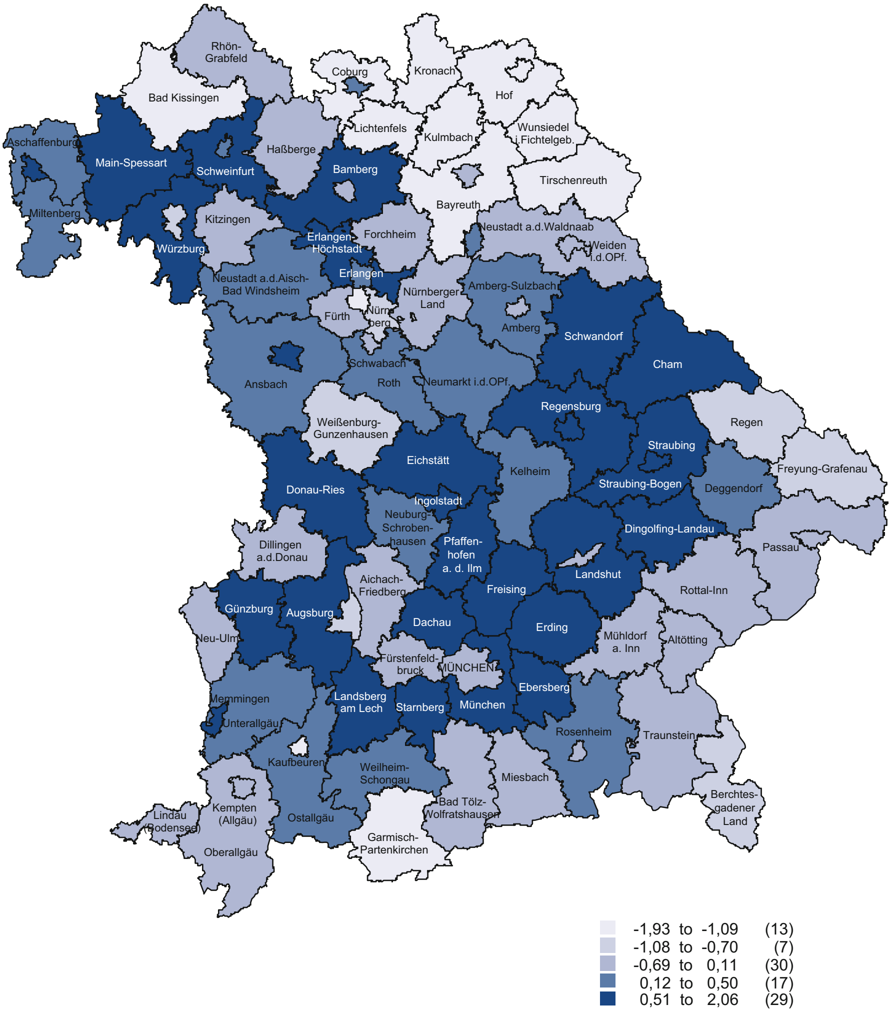
	Employment growth rate	Sectoral effect	Establishment size effect	Qualification effect	Location effect
Kelheim, Distr	0.27	−0.33	0.16	−0.31	1.09
Landshut, Distr	0.95	−0.55	0.28	−0.19	1.75
Passau, Distr	−0.16	−0.51	0.48	−0.40	0.64
Regen, Distr	−0.87	−0.61	0.35	−0.47	0.20
Rottal-Inn, Distr	−0.09	−0.94	0.51	−0.36	1.08
Straubing-Bogen, Distr	0.77	−0.63	0.43	−0.34	1.65
Dingolfing-Landau, Distr	0.81	1.00	−0.62	−0.49	1.27
Oberpfalz					
Amberg, City	−0.59	−0.11	−0.17	−0.22	0.26
Regensburg, City	0.70	0.65	−0.33	0.13	0.57
Weiden i.d.OPf., City	−0.56	−0.45	0.06	−0.32	0.50
Amberg-Sulzbach, Distr	0.49	−0.77	0.17	−0.36	1.79
Cham, Distr	0.87	−0.79	0.34	−0.39	2.04
Neumarkt i.d.OPf., Distr	0.25	−0.84	0.10	−0.29	1.60
Neustadt a.d.Waldnaab, Distr	−0.66	−0.55	0.16	−0.46	0.57
Regensburg, Distr	1.40	−0.36	0.46	−0.20	1.83
Schwandorf, Distr	0.63	−0.19	0.21	−0.41	1.38
Tirschenreuth, Distr	−1.24	−1.09	0.24	−0.45	0.45
Oberfranken					
Bamberg, City	−0.34	−0.13	−0.24	−0.14	0.52
Bayreuth, City	−0.49	−0.02	0.09	−0.11	−0.10
Coburg, City	0.24	0.37	−0.24	−0.06	0.54
Hof, City	−1.72	−0.84	0.23	−0.20	−0.35
Bamberg, Distr	0.61	−0.78	0.45	−0.33	1.64
Bayreuth, Distr	−1.32	−0.81	0.34	−0.39	−0.03
Coburg, Distr	−1.80	−1.18	0.11	−0.51	0.39
Forchheim, Distr	0.01	−0.45	0.33	−0.27	0.76
Hof, Distr	−1.86	−1.69	0.23	−0.34	0.45
Kronach, Distr	−1.37	−0.76	0.21	−0.58	0.18
Kulmbach, Distr	−1.61	−1.05	0.32	−0.32	−0.10
Lichtenfels, Distr	−1.42	−0.87	−0.07	−0.54	0.57
Wunsiedel i. Fichtelgebirge, Distr	−1.93	−0.94	0.17	−0.50	−0.28
Central Franconia					
Ansbach, City	0.52	0.50	−0.04	−0.25	0.66
Erlangen, City	0.41	0.19	−0.65	0.67	0.56
Fürth, City	−1.14	0.04	−0.14	−0.03	−0.57
Nuremberg, City	−0.90	0.50	−0.30	0.04	−0.73
Schwabach, City	−0.68	−0.07	0.35	−0.18	−0.39
Ansbach, Distr	0.20	−0.86	0.30	−0.45	1.62
Erlangen-Höchstadt, Distr	2.06	−0.59	−0.10	−0.10	3.19
Fürth, Distr	−0.65	−0.48	0.59	−0.20	−0.16
Nuremberg Land, Distr	−0.35	−0.27	0.14	−0.16	0.31

(continued)

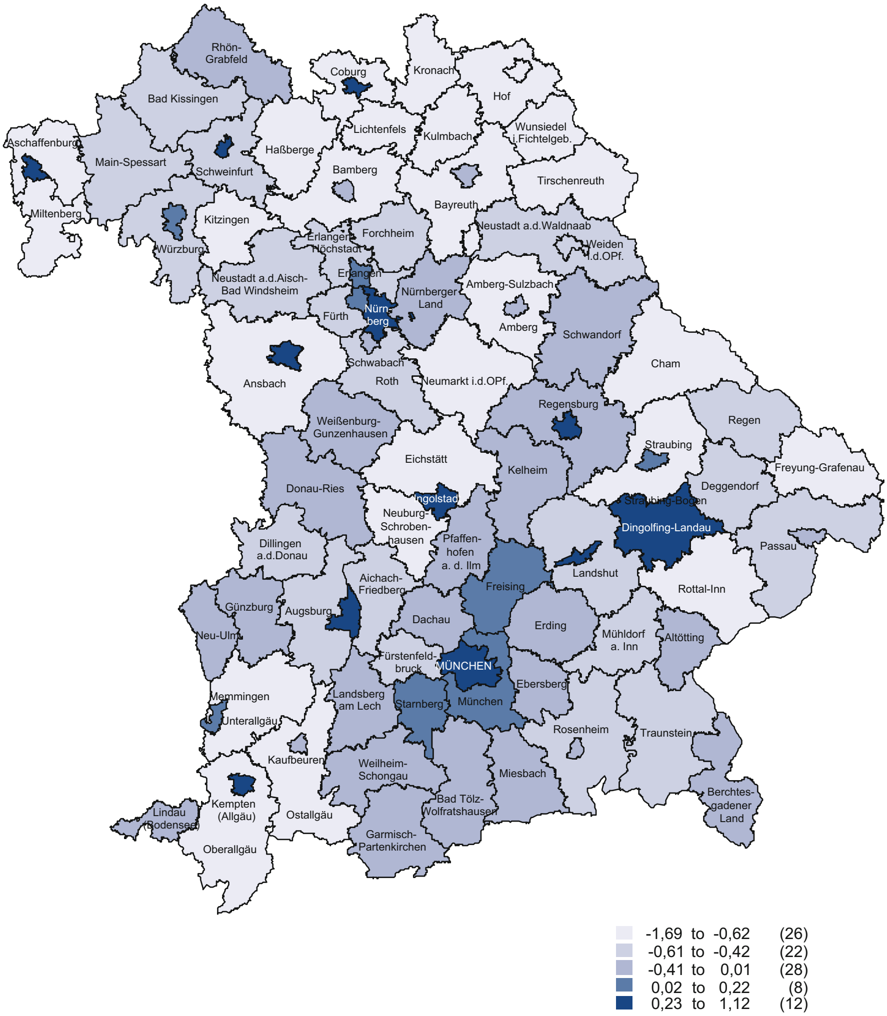
Table 6.8 (continued)

	Employment growth rate	Sectoral effect	Establishment size effect	Qualification effect	Location effect
Neustadt a.d.Aisch-Bad Windsheim, Distr	0.44	−0.56	0.55	−0.35	1.15
Roth, Distr	0.18	−0.61	0.54	−0.23	0.82
Weißenburg-Gunzenhausen, Distr	−0.85	−0.40	0.22	−0.41	0.11
Lower Franconia					
Aschaffenburg, City	0.64	0.50	−0.13	−0.14	0.75
Schweinfurt, City	0.49	0.29	−0.53	−0.14	1.23
Würzburg, City	−0.98	0.22	−0.11	0.03	−0.76
Aschaffenburg, Distr	0.18	−0.65	0.25	−0.12	1.05
Bad Kissingen, Distr	−1.18	−0.48	0.41	−0.31	−0.43
Rhön-Grabfeld, Distr	−0.35	−0.41	0.11	−0.23	0.56
Haßberge, Distr	0.11	−0.71	0.11	−0.42	1.51
Kitzingen, Distr	0.05	−0.63	0.24	−0.25	1.04
Miltenberg, Distr	0.15	−0.67	0.21	−0.35	1.34
Main-Spessart, Distr	0.53	−0.49	0.03	−0.24	1.56
Schweinfurt, Distr	0.67	−0.52	0.56	−0.29	1.28
Würzburg, Distr	1.31	−0.58	0.45	−0.10	1.89
Swabia					
Augsburg, City	−0.78	0.42	−0.31	0.00	−0.53
Kaufbeuren, City	−1.25	−0.30	0.39	−0.17	−0.78
Kempten (Allgäu), City	0.01	0.34	0.18	−0.14	−0.05
Memmingen, City	0.79	0.08	−0.10	−0.25	1.33
Aichach-Friedberg, Distr	0.03	−0.58	0.41	−0.29	0.93
Augsburg, Distr	0.74	−0.57	0.37	−0.20	1.50
Dillingen a.d.Donau, Distr	−0.27	−0.42	0.18	−0.45	0.76
Günzburg, Distr	0.57	−0.29	0.10	−0.31	1.41
Neu-Ulm, Distr	−0.11	−0.17	0.04	−0.22	0.60
Lindau (Bodensee), Distr	−0.01	−0.34	0.18	−0.21	0.69
Ostallgäu, Distr	0.27	−0.67	0.35	−0.30	1.24
Unterallgäu, Distr	0.24	−0.81	0.28	−0.27	1.37
Donau-Ries, Distr	0.75	−0.33	−0.03	−0.31	1.71
Oberallgäu, Distr	−0.29	−0.64	0.44	−0.21	0.48

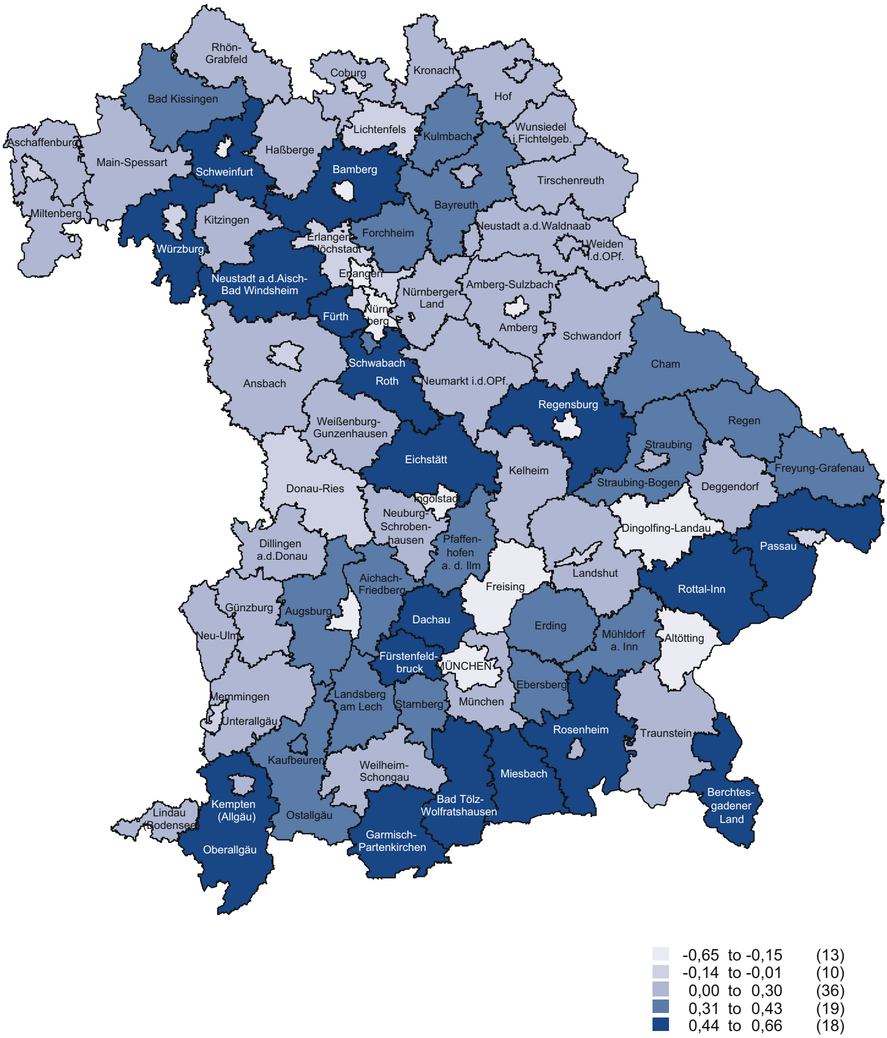
Source: Statistics of the Federal Employment Agency and IAB Employment History; own calculations



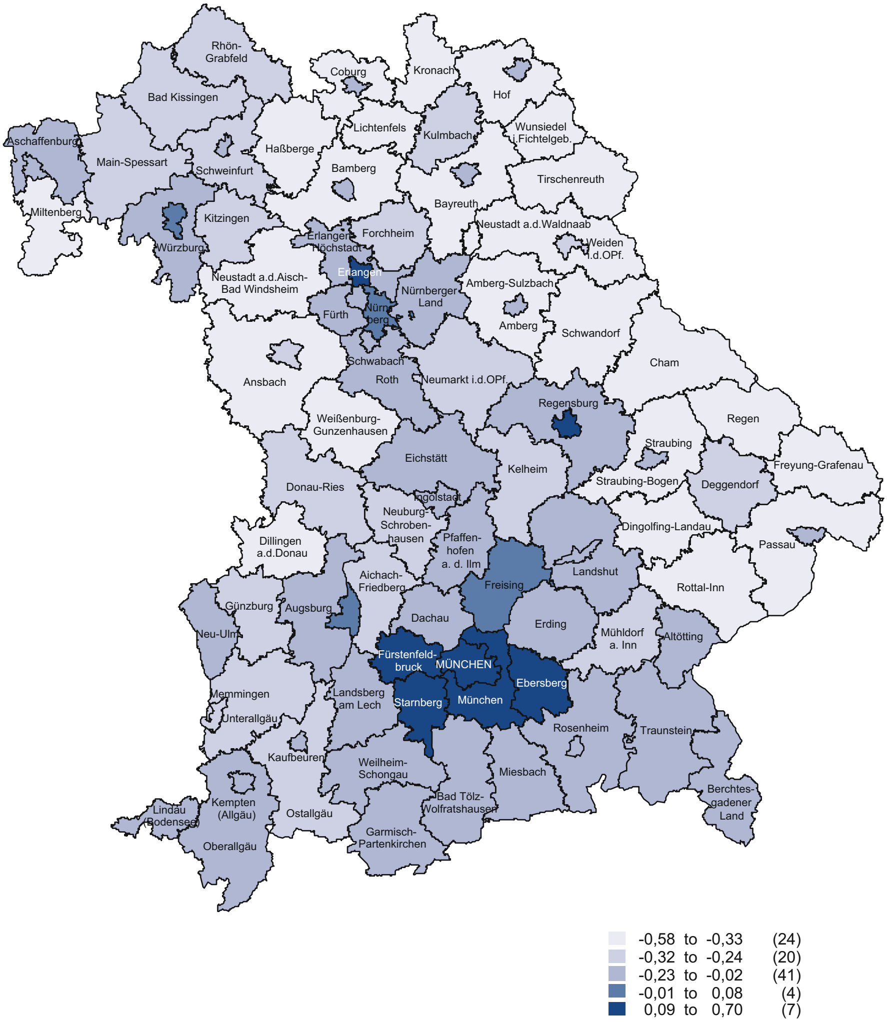
Map 6.1 Employment development 1993–2008 (annual average growth rate in %)



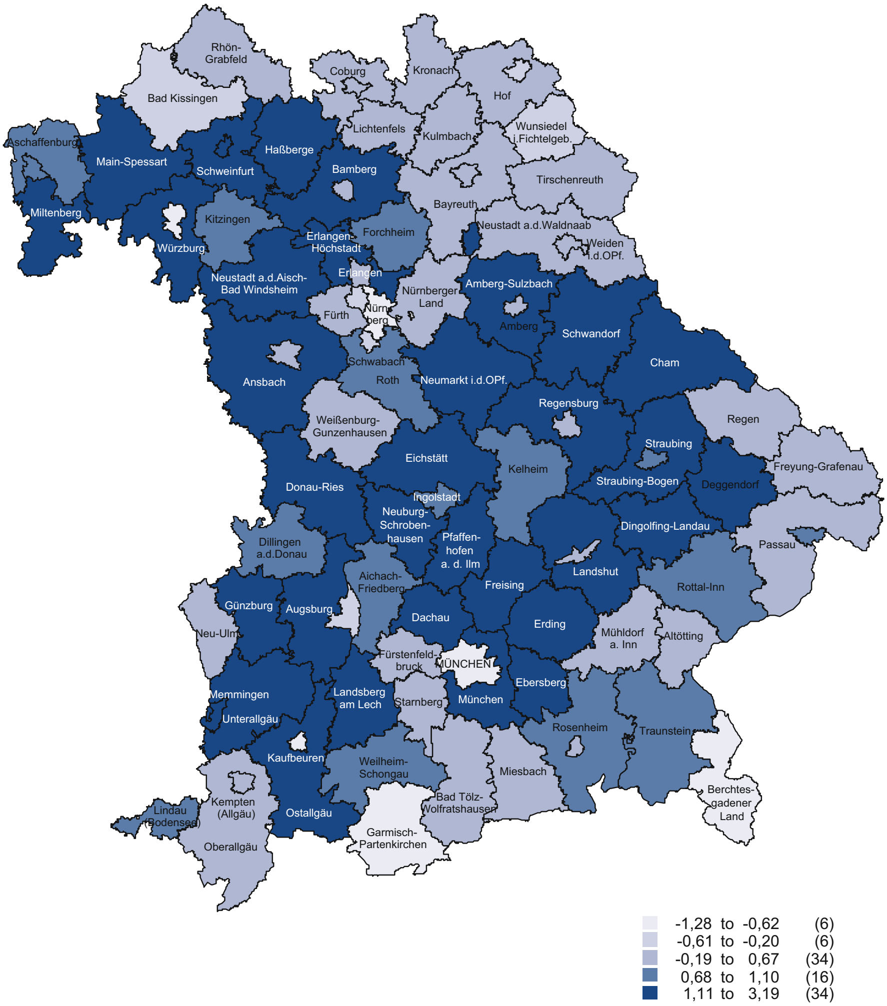
Map 6.2 Influence of the sectoral determinant in Bavarian districts



Map 6.3 Influence of the establishment size determinant in Bavarian districts



Map 6.4 Influence of the qualification determinant in Bavarian districts



Map 6.5 Influence of the location determinant in Bavarian districts

References

Acemoglu D (2002) Technical change, inequality and the labour market. J Econ Litt 40:7–72

Acs ZJ, de Groot H, Nijkamp P (eds) (2002) The emergence of the knowledge economy. A regional perspective. Springer, Berlin

Amend E, Otto A (2006) Die Determinanten der Beschäftigungsentwicklung im VALA-Modell. Sozialer Fortschritt 55:268–272

Appelbaum E, Schettkat R (1999) Are prices unimportant? J Post Keynes Econ 21:387–398

Autor DH, Levy F, Murnane RJ (2003) The skill content of recent technological change: an empirical exploration. Q J Econ 118:1279–1333

Badinger H, Tondl G (2005) The factor behind European regional growth: trade, human capital and innovation. Jahrbuch für Regionalwissenschaft 25:67–89

Blien U, Sanner H (2006) Structural change and regional employment dynamics. IAB discussion paper no. 06–06, Nürnberg

Blien U, Suedekum J (2007) Stimulating employment growth with higher wages? Kyklos 60:441–464

Blien U, Wolf K (2002) Regional development of employment in eastern Germany: an analysis with an econometric analogue to shift-share techniques. Pap Reg Sci 81:391–414

Blien U, Maierhofer E, Vollkommer D, Wolf K (2003) Einflussfaktoren der Entwicklung ostdeutscher Regionen. Theorie, Daten, Deskriptionen und quantitative Analysen. In: Blien U (ed) Die Entwicklung der ostdeutschen Regionen. Beiträge zur Arbeitsmarkt- und Berufsforschung, 267. Bundesanstalt für Arbeit, Nürnberg

Blien U, Suedekum J, Wolf K (2006) Local employment growth in west Germany: a dynamic panel approach. Labour Econ 13(4):445–458

Blien U et al (incl. Eigenhüller L, Promberger M) (2011) Bericht der Arbeitsgruppe 1 “Regionale Arbeitsmärkte – Wirtschaftsstrukturpolitik” der Kommission “Anforderungen aus dem zweiten Bayerischen Sozialbericht”, München

Böhme S, Eigenhüller L (2005) Vergleichende analyse von Länderarbeitsmärkten. Länderstudie Bayern. IAB Regional IAB Bayern 05–01, Nürnberg

Buch T, Hamann S, Niebuhr A (2010) Wanderungsbilanzen deutscher Metropolen: der Wettbewerb um kluge Köpfe nimmt zu. IAB-Kurzbericht 10–16, Nürnberg

Chiang S (2012) Shift-share analysis and international trade. Ann Reg Sci 49:571–588

Cingano F, Schivardi F (2004) Identifying the sources of local productivity growth. J Eur Econ Assoc 2:720–742

Dauth W (2013) Agglomeration and regional employment dynamics. Pap Reg Sci 92:419–435

Dunn ES (1960) A statistical and analytical technique for regional analysis. Pap Reg Sci Assoc 6:97–112

Eigenhüller L (2006) Spezifische regionale Bedingungen als Standortvorteil Bayerns. Sozialer Fortschritt 55:280–283

Farhauer O, Kröll A (2012) Diversified specialisation – going one step beyond regional economics’ specialisation-diversification concept. Jahrbuch für Regionalwissenschaft 32:63–84

Fujita M, Krugman P, Venables A (1999) The spatial economy: cities, regions, and international trade. MIT Press, Cambridge MA/London

Glaeser E, Gottlieb J (2009) The wealth of cities: agglomeration economies and spatial equilibrium in the United States. J Econ Litt 47(4):983–1028

Greene W, Seaks T (1991) The restricted least squares estimator. Rev Econ Stat 73:563–567

Haisken-DeNew JP, Schmidt CM (1997) Inter-industry and inter-region differentials: mechanics and interpretation. Rev Econ Stat 79:516–521

Knudsen DC, Barff R (1991) Shift-share analysis as a linear model. Environ Plan A 23:421–431

Kowalewski J (2011) Specialization and employment development in Germany: an analysis at the regional level. Pap Reg Sci 90:789–811

Krugman P (1991) Geography and trade. MIT Press, Cambridge, MA

Longhi S, Nijkamp P, Traistaru I (2005) Is sectoral diversification a solution to unemployment? Evidence from EU regions. Kyklos 58(4):591–610

Loveridge S, Selting AC (1998) A review and comparison of shift-share identities. Int Reg Sci Rev 21(1):37–58

Ludsteck J (2006) VALA – das ökonometrische modell. Sozialer Fortschritt 55:272–275

Möller J (1995) Unweighted and weighted measures of inter-industry wage variability – a technical note, unpublished paper of the University, Regensburg

Möller J, Tassinopoulos A (2000) Zunehmende Spezialisierung oder Strukturkonvergenz? Eine Analyse der sektoralen Beschäftigungsentwicklung auf regionaler Ebene. Jahrbuch für Regionalwissenschaft 20:1–38

Neisser H (1942) ‘Permanent’ technological unemployment. Demand for commodities is not demand for labor. Am Econ Rev 32:50–71

Patterson MG (1991) A note on the formulation of the full-analogue regression model of the shift-share method. J Reg Sci 31:211–216

Promberger M (2012) Mythos der Vollbeschäftigung und Arbeitsmarkt der Zukunft. Aus Politik und Zeitgeschichte 14(15):30–38

Schanne N (2011) VALA reloaded – internal technical manual. Institut für Arbeitsmarkt- und Berufsforschung, Nürnberg

Suedekum J, Blien U, Ludsteck J (2006) What has caused regional employment growth differences in Eastern Germany? Jahrbuch für Regionalwissenschaft 26:51–73

Zierahn U (2012) The importance of spatial autocorrelation for regional employment growth in Germany. Jahrbuch für Regionalwissenschaft 32:19–43

Chapter 7
Classic and Spatial Shift-Share Analysis of State-Level Employment Change in Brazil

Valente J. Matlaba, Mark Holmes, Philip McCann, and Jacques Poot

7.1 Introduction

The Brazilian economy has gone through a remarkable transformation since the difficult times of the last quarter of the twentieth century. Brazil is now seen as one of the engines of global economic growth and together with Russia, India and China makes up the often cited BRIC acronym. During the current decade, Brazil is expected to overtake the economies of Britain and France and become the world's fifth largest economy, with São Paulo possibly the world's fifth wealthiest city.

Such rapid national development begs the question of whether the benefits are being reaped in all regions, with poorer ones catching up, or whether the gap

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V.J. Matlaba (✉)
Vale Technological Institute, Rua Boaventura da Silva, 955, CEP 66055-090 Umarizal, Belém, PA, Brazil
e-mail: valente.matlaba@yahoo.com.br

M. Holmes
Department of Economics, University of Waikato, P.O. Box 3105, Hamilton 3240, New Zealand
e-mail: holmesmj@waikato.ac.nz

P. McCann
Faculty of Spatial Sciences, University of Groningen, Landleven 1, 9747 AD Groningen, The Netherlands
e-mail: P.McCann@rug.nl

J. Poot
National Institute of Demographic and Economic Research (NIDEA), University of Waikato, Private Bag 3105, Hamilton, New Zealand
e-mail: jpoot@waikato.ac.nz

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between the rich and poor regions is widening. At present, Gross State Product (GSP) per capita in Rio de Janeiro and São Paulo is 50 % higher than Brazil's Gross Domestic Product (GDP) per capita, but in the northeastern states of Piaui and Maranhão, GSP per capita is less than 30 % of Brazil's GDP per capita.

To address such a question one would ideally carry out a formal econometric analysis along the lines of neoclassical or endogenous growth models (e.g. Barro and Sala-i-Martin 2004). Alternatively, one might consider the dynamic adjustments suggested by models of the New Economic Geography (e.g. Brakman et al. 2001). In either case, a first requirement is the availability of reliable regional production data at sectoral and aggregate levels, plus a range of socio-economic indicators. In Brazil such subnational accounts data have been, until recently, rather incomplete or difficult to compare over time.

However, sub-national demographic and employment data are available on a consistent basis for several decades. In another paper (Matlaba et al. 2012), we exploited such data to identify the impact of Marshall-Arrow-Romer, Porter and Jacobs' externalities in manufacturing by means of the Glaeser et al. (1992) approach. Here we take a broader approach to analyse state growth in Brazil and consider all production sectors simultaneously. We accept that ideally we would have calculated measures of total factor productivity growth (e.g. Cingano and Schivardi 2004) but, in the absence of the required regional data, we follow the example of Glaeser et al. (1992) of using regional-sectoral employment as a proxy for regional economic activity.

For this purpose this chapter starts with the conventional shift-share accounting framework, which decomposes total growth in a region in terms of national, industry-mix, and competitive shift effects (Dunn 1960; Esteban-Marquillas 1972; Arcelus 1984; Berzeg 1978, 1984; Haynes and Machunda 1987; Dinc et al. 1998; Dinc and Haynes 1999). Despite criticisms and various alternative formulations, the classic shift-share approach remains popular after half a century of application (Knudsen and Barff 1991; McDonough and Sihag 1991; Loveridge 1995; Knudsen 2000).

This approach is extended in this chapter in five ways. First, we track the classic shift-share components over five consecutive quinquennia, starting in 1981. This provides a dynamic perspective on the shift-share decomposition.[1] Secondly, we define and calculate a new structural change effect to show that most states have been creating jobs in industries that nationally became more prominent and shed jobs in industries that contracted nationally, i.e. states generally did not go against the trends. Thirdly, we calculate a wide range of alternative shift-share decompositions proposed in the literature to show that these refinements lead to interpretations that remain very similar to those of classic shift-share analysis. Fourthly, we identify the spatial patterns in the shift-share decomposition by means of exploratory spatial data analysis (ESDA). Fifthly, we use Nazara and Hewings's (2004) spatial shift-share taxonomy to add a spatial component for each

[1] However, we do not use regression methods for shift-share analysis. This alternative approach was originally proposed by Patterson (1991).

state into the shift-share decomposition, namely a measure of spatially weighted employment growth in surrounding states. Nazara and Hewings also introduce additional industry-specific spatial components into shift-share, but because the focus of this chapter is on regional aggregates rather than individual industries, our spatial shift-share taxonomy can be simplified to a four-component decomposition. In this decomposition, the spatial component has an intuitively attractive interpretation, namely the regional rate of growth one might expect in the presence of full spatial spillover of growth in surrounding regions, after controlling for national industry-specific growth. Although the focus of the chapter is the application of the various shift-share techniques to the case of Brazil, the methodology can clearly also be applied to other countries.

Together with the classic shift-share decomposition, the spatial analysis suggests a catching up of peripheral regions in Brazil, although agglomeration effects ensure that the dominance of the states of the south east remains. The results of this dynamic and spatial shift-share analysis are therefore consistent with those of the econometric literature on regional development in Brazil (see e.g. Rolim 2008; Daumal and Zignago 2010).

The period under consideration is 1981–2006. The reasons for the choice of this period are twofold. First, the available sub-national data are complete and consistent for this period only. Secondly, this period covers a wide range of socio-economic and political conditions in Brazilian economic history: economically, it includes sub-periods of depression (1981–1983; 1986–1993) and prosperity (1984–1985; 1994–2006); politically, it includes dictatorship (1981–1984), democracy (1990–2006), and a combination of both regimes (1985–1989); institutionally, in addition to political changes themselves, it presents a sub-period of a relatively closed economy from 1981 to 1989 and another of a gradual trade liberalisation since 1989 (Lobo 1996; Abreu 2008a, b; Abreu and Werneck 2008). It will be shown later in this chapter that the fundamental driving forces of growth (or decline) as measured by dynamic spatial shift-share analysis remain robust under such dramatically changing circumstances.

Shift-share studies of growth in various countries often only consider non-spatial effects. This is also the case for Brazil (Rolim 2008; Chahad et al. 2002). Some studies incorporate implications of international trade for the regional economy in the shift-share method (Markusen et al. 1991; Gazel and Schwer 1998; Dinc and Haynes 2005) but the analysis is not developed in that direction in this chapter, given that Brazil's international trade accounted over the period considered for no more than 24 % of GDP (and was in fact 60 years earlier higher than during the 1981–2006 period). Instead, this chapter integrates the non-spatial classic shift-share methodology with ESDA of the shift-share components (Cochrane and Poot 2008; Le Gallo and Kamarianakis 2011) and the methodology developed in Nazara and Hewings (2004), which explicitly incorporates spatial effects in the shift-share taxonomy to explain growth of regions.[2]

7.2 Classic Multi-Period Shift-Share Analysis

This section briefly presents the classic shift-share method. This method decomposes the change in employment as follows (e.g., Cochrane and Poot 2008, p. 55):

$$\Delta E_{ir}^{t} \equiv E_{ir}^{t} - \mathrm{E}_{ir}^{t-1} \equiv NE_{ir}^{t} + IM_{ir}^{t} + CE_{ir}^{t} \tag{7.1}$$

where:

$$NE_{ir}^{t} = g_{00}^{t}\ E_{ir}^{t-1} \tag{7.2}$$

$$IM_{ir}^{t} = \left(g_{i0}^{t} - g_{00}^{t}\right)\ E_{ir}^{t-1} \tag{7.3}$$

$$CE_{ir}^{t} = \left(g_{ir}^{t} - g_{i0}^{t}\right)\ E_{ir}^{t-1} \tag{7.4}$$

The terms in the above equations are defined as:

E_{ir}^{t-1} = Employment in the i^{th} industry in the r^{th} region at time $t-1$.

E_{ir}^{t} = Employment in the i^{th} industry in the r^{th} region at time t.

NE_{ir}^{t} = National Growth Effect on industry i in the r^{th} region between $(t-1)$ and t.

IM_{ir}^{t} = Industry-Mix Effect on industry i in the r^{th} region between $(t-1)$ and t.

CE_{ir}^{t} = Competitive Effect on industry i in the r^{th} region between $(t-1)$ and t.

g_{ir}^{t} = Growth rate of employment in industry i and region r between $(t-1)$ and t.

g_{i0}^{t} = Growth rate of nationwide employment in industry i between $(t-1)$ and t.

g_{00}^{t} = Growth rate in nationwide total employment between $(t-1)$ and t.

When we aggregate employment in each region r over industries i and define g_{0r}^{t} as the growth rate of total employment in region r between times $(t-1)$ and t, this growth rate can be decomposed into a national growth rate; a growth rate due to the

[2] Mitchell et al. (2005) apply Nazara and Hewings's (2004) spatial shift-share decomposition to data on Australian regions. Mayor and López (2008) combined a variety of spatial analysis tools with the shift-share method.

industry-mix and a residual that is referred to as the competitive growth rate c_{0r}^t. Hence,

$$g_{0r}^t \equiv g_{00}^t + m_{0r}^t + c_{0r}^t \tag{7.5}$$

in which the growth component due to industry-mix is defined by

$$m_{0r}^t \equiv \sum_i s_{ir}^{t-1}(g_{i0}^t - g_{00}^t) \tag{7.6}$$

with s_{ir}^{t-1} the fraction of employment in region r that is in industry i at time $(t-1)$, i.e. $s_{ir}^{t-1} = E_{ir}^{t-1}/E_{0r}^{t-1}$. Equation (7.6) shows that the industry-mix growth rate is a weighted average of national sectoral growth rates, minus national aggregate growth, with the weights being the shares of the various sectors in regional employment at the beginning of the period under consideration.

7.3 Data and Sources

This chapter uses employment data which we obtained from IPEA – Institute of Applied Economic Research (www.ipea.gov.br). IPEA makes available a variety of socio-economic data collected from public and private Brazilian institutions, mostly at the state level.

Data have been collected for all 27 states (including Distrito Federal; for states' boundaries, see Fig. 7.1). Information on the number of employed people in each state by sector was extracted from 1981 to 2006. The sectors are: (1) agriculture and fishing; (2) commerce; (3) construction; (4) electricity, water and gas; (5) finance; (6) manufacturing; (7) mining; (8) services; and (9) transportation and communications.

The five selected periods to analyze employment growth are: 1981–1986, 1986–1991, 1991–1996, 1996–2001, and 2001–2006. Although there are data to calculate annual changes, the use of 5-year periods provides some control for cyclical employment fluctuations (see Barff and Knight 1988, pp. 3–4). By using periods of equal duration we take account of the issue that varying periods may lead to the risk of an undue influence of sudden employment (or income) changes in atypical years (Barff and Knight 1988, p. 6; Knudsen and Barff 1991, pp. 427–428; Knudsen 2000, pp. 179–180).

There are missing employment data for all states in 1991. To address this problem, we simply interpolated the distribution of employment across sectors between 1990 and 1992 and we subsequently applied the interpolated shares to the known state total employment. Additionally, there were missing employment data for Tocantins from 1981 to 1991. Here we assumed that total employment growth was identical to known state population growth over the sub-periods

Fig. 7.1 Brazil's states boundaries – 26 states plus Distrito Federal (Source: http://www.brazilmycountry.com/brazil-map.html#regions%20map)

1981–1986, 1986–1991, and 1991–1996. We assumed sectoral shares in Tocantins to have been the same in 1981, 1986, and 1991 as observed in 1996.[3]

7.4 Results of Classic Shift-Share Analysis

This section outlines the main characteristics of the events that shaped the performance of the Brazilian economy from 1981 to 2006; then, using employment data, it presents the results of the non-spatial shift-share analysis. In terms of the economic history of Brazil, 1981–2006 can be subdivided into three periods as follows.

[3] An alternative assumption would have been to backcast the 1981–1991 Tocantins sectoral shares from 1996 by means of the observed trends in national sectoral shares. This has very little impact on the results reported in the tables in this chapter.

Period I: 1981–1984 (the final part of the dictatorship or "Authoritarian State" period, which started in 1964). The main characteristics are (Lobo 1996; Fausto 1999; Abreu 2008a): (i) the combination of economic stagnation and inflation ('stagflation'); (ii) little political rights and freedom; (iii) oil shocks (1974–1980) causing macroeconomic instability; (iv) economic redistribution that harmed the northeast and benefited the middle-west, north and south regions; (v) protectionism, contractionist policies, and falling output (1981–1983).

Period II: 1985–1989 (democratic transition). This period is characterized by poor economic performance as a result of hyperinflation and stagnation.

Period III: 1989–2006 (Trade liberalization and the return to democracy). The main facts are (Lobo 1996; Abreu 2008b; Abreu and Werneck 2008): (i) the structural reforms under the Collor de Mello (1990–1992) and Itamar Franco (1992–1994) presidencies; (ii) the policies that aimed to reduce and stabilize inflation and unemployment were more successful after mid-1994; however, (iii) as Abreu and Werneck (2008, p. 432) point out, "(. . .) between 1994 and 2004 per capita GDP (gross domestic product) increased [at] an average of only 0.9 percent per annum".

A comparison of national and sectoral employment growth with productivity growth across the 5-year sub-periods shows that the periods 1981–1986 and 1996–2001 stand out in that GDP per capita growth declined even though employment increased (Table 7.1). Services, commerce and transportation, and communications are industries that had significant employment growth throughout the 1981–2006 period. Employment change was rather volatile in the other sectors. Table 7.1 reports the trends in regional and state employment shares. This shows that the employment shares of the North Region and the Center-West Region have been growing, while the employment shares of the South Region and the Southeast Region have been declining. The share of the Northeast Region remained around 27 % throughout the 1981–2006 period. The shift-share methodology in this chapter focusses essentially on the dynamics and spatial spillovers of the interactions between the sectoral trends in Table 7.1 and the regional trends in Table 7.1.

Table 7.2 provides the classic shift-share decomposition of total employment growth in Brazil's states in terms of the national, industry-mix and competitive components for the five sub-periods.[4] The states have been ranked according to the five-period average total employment growth rate (from high to low). Roraima had the highest average 5-year growth rate (75.1 %) and Rio de Janeiro the lowest (10.9 %).

[4] To calculate the employment growth rates, several assumptions have been made. There are states with zero sectoral employment as follows: for mining: Acre in 1981, 1986, 1996, 2001, and 2006; Alagoas in 1996, Roraima in 1981, and for Amapá in 1986 and 1996. For finance: Amapá in 1996. In these cases we used the population growth rate as a proxy for employment growth over the sub-periods to estimate sectoral employment in each of those years. The assumptions we made yielded results that are consistent with the overall pattern of employment data in Brazil. However, due to a lack of state population data for 1981 and 1986, we estimated the population in those years by interpolation within the available population time series.

Table 7.1 Employment growth in Brazil, 1981–2006

	% shares 1981	1981–1986 change (%)	1986–1991 change (%)	1991–1996 change (%)	1996–2001 change (%)	2001–2006 change (%)
(a) Sectoral employment shares and sectoral employment growth						
Agriculture and Fishing	32.2	5.7	13.1	2.0	−5.0	10.6
Commerce	11.2	29.8	28.1	15.8	19.6	44.4
Construction	8.7	−4.9	9.9	13.4	14.4	17.6
Electricity, Water and Gas	0.8	9.5	4.5	−8.7	−2.7	18.3
Financial Sector	2.1	20.1	−3.2	−20.1	−1.9	127.5
Manufacturing	15.5	27.5	1.0	−3.0	9.5	38.6
Mining	0.6	40.5	−5.0	−40.8	22.8	46.3
Services	24.6	30.8	26.5	20.4	19.2	23.2
Transportation and Communications	4.3	9.7	20.5	11.1	24.6	22.8
National employment growth rate	**–**	**18.9**	**16.7**	**8.9**	**12.2**	**17.7**
GDP per capita growth rate	**–**	**−2.4**	**7.4**	**12.9**	**−9.8**	**12.2**
(b) Regional employment shares						
State	1981	1986	1991	1996	2001	2006
Acre	0.1 %	0.2 %	0.2 %	0.2 %	0.2 %	0.3 %
Amazonas	0.7 %	0.8 %	0.9 %	0.9 %	1.1 %	1.6 %
Amapá	0.1 %	0.1 %	0.1 %	0.2 %	0.2 %	0.3 %
Pará	1.2 %	1.4 %	1.6 %	1.7 %	2.3 %	3.5 %
Rondônia	0.2 %	0.4 %	0.5 %	0.5 %	0.5 %	0.9 %
Roraima	0.0 %	0.1 %	0.1 %	0.1 %	0.1 %	0.2 %
Tocantins	0.7 %	0.6 %	0.8 %	0.7 %	0.8 %	0.7 %
North region	**3.0 %**	**3.5 %**	**4.1 %**	**4.3 %**	**5.2 %**	**7.5 %**
Alagoas	1.5 %	1.5 %	1.6 %	1.3 %	1.5 %	1.4 %
Bahia	7.5 %	7.7 %	7.8 %	7.4 %	7.4 %	7.2 %
Ceará	4.1 %	4.2 %	4.2 %	4.3 %	4.4 %	4.3 %
Maranhão	3.2 %	3.0 %	3.1 %	3.7 %	3.5 %	3.1 %
Paraíba	2.0 %	2.0 %	2.0 %	2.1 %	1.8 %	1.9 %

Pernambuco	4.8 %	4.6 %	4.6 %	4.4 %	4.4 %	4.1 %
Piauí	1.7 %	1.6 %	1.7 %	1.8 %	1.7 %	1.8 %
Rio Grande do Norte	1.3 %	1.4 %	1.5 %	1.5 %	1.5 %	1.5 %
Sergipe	1.0 %	1.0 %	1.0 %	1.0 %	1.0 %	1.0 %
Northeast region	**27.0 %**	**27.0 %**	**27.5 %**	**27.5 %**	**27.3 %**	**26.4 %**
Distrito Federal	0.5 %	1.1 %	1.1 %	1.1 %	1.2 %	1.2 %
Goiás	2.5 %	2.1 %	2.5 %	3.1 %	3.2 %	3.1 %
Mato Grosso do Sul	1.2 %	1.3 %	1.3 %	1.3 %	1.3 %	1.3 %
Mato Grosso	0.9 %	1.1 %	1.5 %	1.5 %	1.7 %	1.6 %
Center-West region	**5.1 %**	**5.6 %**	**6.4 %**	**7.0 %**	**7.4 %**	**7.2 %**
Espírito Santo	1.8 %	1.8 %	1.9 %	1.9 %	2.0 %	2.0 %
Minas Gerais	11.2 %	11.2 %	11.3 %	11.2 %	11.1 %	11.1 %
Rio de Janeiro	9.8 %	9.4 %	8.7 %	8.4 %	7.9 %	7.5 %
São Paulo	23.5 %	23.9 %	22.2 %	22.3 %	22.0 %	21.9 %
Southeast region	**46.1 %**	**46.3 %**	**44.1 %**	**43.8 %**	**43.0 %**	**42.5 %**
Paraná	7.3 %	6.7 %	6.5 %	6.5 %	6.3 %	6.1 %
Santa Catarina	3.5 %	3.5 %	3.5 %	3.5 %	3.8 %	3.7 %
Rio Grande do Sul	8.0 %	7.4 %	7.5 %	7.3 %	7.1 %	6.6 %
South region	**18.7 %**	**17.6 %**	**17.5 %**	**17.3 %**	**17.2 %**	**16.4 %**
Brazil's total employment (millions of people)	43.9	52.2	60.9	66.3	74.4	87.6

Notes: An estimate of the national population in 1981 is 122.5 million (based on interpolation of population census data from IBGE – Brazilian Institute of Geography and Statistics, www.ibge.gov.br). The average 5-year real GDP per capita growth rate from 1981 to 2006 is 4.1 %

Table 7.2 Classic shift-share decomposition of total employment growth rate in Brazil's States

	1981–1986				1986–1991				1991–1996				1996–2001				2001–2006				Five-period averages			
State[a]	g_{0r}^{86}	g_{00}^{86}	m_{0r}^{86}	c_{0r}^{86}	g_{0r}^{91}	g_{00}^{91}	m_{0r}^{91}	c_{0r}^{91}	g_{0r}^{96}	g_{00}^{96}	m_{0r}^{96}	c_{0r}^{96}	g_{0r}^{01}	g_{00}^{01}	m_{0r}^{01}	c_{0r}^{01}	g_{0r}^{06}	g_{00}^{06}	m_{0r}^{06}	c_{0r}^{06}	g_{0r}	g_{00}	m_{0r}	c_{0r}
Roraima	121.8	17.7	1.7	102.4	62.7	16.2	3.2	43.4	54.9	9.1	2.7	43.1	37.0	11.1	5.0	20.9	99.4	26.5	0.0	72.9	75.1	16.1	2.5	56.5
Rondônia	114.7	17.7	3.3	93.8	40.1	16.2	2.9	21.0	8.1	9.1	2.4	−3.3	28.2	11.1	3.9	13.2	121.4	26.5	1.0	94.0	62.5	16.1	2.7	43.7
Amapá	48.2	17.7	4.2	26.2	56.7	16.2	5.1	35.5	98.2	9.1	4.9	84.2	20.0	11.1	3.7	5.2	87.1	26.5	2.4	58.2	62.0	16.1	4.0	41.9
Acre	96.3	17.7	5.5	73.1	30.5	16.2	4.4	10.0	16.4	9.1	3.8	3.6	34.0	11.1	5.0	18.0	123.5	26.5	0.0	97.1	60.2	16.1	3.7	40.3
Distrito Federal	150.6	17.7	5.5	127.4	24.5	16.2	4.1	4.3	8.3	9.1	4.5	−5.3	24.8	11.1	5.1	8.6	43.8	26.5	4.1	13.1	50.4	16.1	4.7	29.6
Pará	39.3	17.7	4.0	17.5	36.3	16.2	2.9	17.2	16.2	9.1	2.6	4.5	53.3	11.1	3.0	39.2	95.2	26.5	2.1	66.7	48.1	16.1	2.9	29.0
Amazonas	42.1	17.7	4.8	19.6	36.7	16.2	−0.1	20.6	13.0	9.1	1.5	2.4	26.1	11.1	3.4	11.5	93.0	26.5	3.0	63.5	42.2	16.1	2.5	23.5
Tocantins	12.7	17.7	−7.2	2.1	12.0	16.2	0.3	−4.4	98.6	9.1	−4.0	93.4	22.0	11.1	−3.2	14.1	26.2	26.5	−4.7	4.4	34.3	16.1	−3.8	21.9
Mato Grosso	52.0	17.7	−1.8	36.1	53.0	16.2	−0.4	37.2	10.7	9.1	−1.7	3.3	24.1	11.1	−1.7	14.7	16.4	26.5	−2.0	−8.0	31.2	16.1	−1.5	16.7
Rio Grande do Norte	23.7	17.7	−1.0	7.0	25.2	16.2	0.6	8.5	11.8	9.1	0.2	2.5	10.4	11.1	−0.6	−0.1	26.7	26.5	−1.4	1.6	19.6	16.1	−0.4	3.9
Mato Grosso do Sul	24.1	17.7	−0.6	7.0	20.7	16.2	1.9	2.7	11.9	9.1	1.5	1.4	8.8	11.1	−0.6	−1.7	28.4	26.5	−0.4	2.3	18.8	16.1	0.4	2.3
Espírito Santo	16.6	17.7	−3.0	1.8	24.3	16.2	−0.3	8.4	9.2	9.1	−0.8	0.8	15.0	11.1	−1.1	5.0	27.3	26.5	−1.5	2.3	18.5	16.1	−1.3	3.7
Sergipe	12.2	17.7	−2.8	−2.8	16.4	16.2	−0.7	1.0	13.2	9.1	−0.9	5.0	7.2	11.1	−1.2	−2.7	36.4	26.5	−2.2	12.1	17.1	16.1	−1.5	2.5
Santa Catarina	20.1	17.7	−1.8	4.2	16.4	16.2	−2.2	2.4	7.8	9.1	−2.5	1.2	17.8	11.1	−2.0	8.7	22.2	26.5	1.4	−5.6	16.9	16.1	−1.4	2.2
Piauí	8.8	17.7	−7.8	−1.1	24.1	16.2	−0.7	8.6	15.1	9.1	−1.7	7.7	7.4	11.1	−4.7	1.0	28.4	26.5	−5.7	7.5	16.8	16.1	−4.1	4.8
Ceará	20.6	17.7	−3.0	5.9	16.7	16.2	−0.5	1.0	12.3	9.1	−0.6	3.7	12.7	11.1	−3.3	5.0	21.3	26.5	−1.9	−3.3	16.7	16.1	−1.9	2.5
Goiás	0.1	17.7	−0.7	−16.9	40.7	16.2	1.4	23.2	2.1	9.1	0.9	−7.9	15.4	11.1	0.5	3.8	23.8	26.5	0.0	−2.8	16.4	16.1	0.4	−0.1
Minas Gerais	19.0	17.7	−1.1	2.4	17.4	16.2	0.5	0.8	8.2	9.1	−0.2	−0.7	9.8	11.1	−0.5	−0.8	25.2	26.5	−1.3	0.1	15.9	16.1	−0.5	0.3
Alagoas	15.7	17.7	−4.6	2.6	20.5	16.2	−1.0	5.3	−7.1	9.1	−1.4	−14.7	32.1	11.1	−3.6	24.6	16.6	26.5	−5.5	−4.4	15.6	16.1	−3.2	2.7
Maranhão	13.2	17.7	−6.4	1.9	19.8	16.2	−0.8	4.5	29.8	9.1	−2.5	23.2	3.9	11.1	−6.7	−0.5	10.9	26.5	−6.0	−9.5	15.5	16.1	−4.5	3.9
Paraíba	19.9	17.7	−4.2	6.4	16.2	16.2	1.3	−1.2	13.2	9.1	−0.3	4.3	−3.4	11.1	−3.0	−11.5	31.4	26.5	−3.0	7.9	15.4	16.1	−1.9	1.2
Bahia	20.5	17.7	−4.2	6.9	18.8	16.2	−0.1	2.7	3.5	9.1	−1.1	−4.4	10.8	11.1	−3.8	3.4	22.1	26.5	−4.5	0.1	15.1	16.1	−2.7	1.7
São Paulo	20.0	17.7	4.6	−2.3	8.2	16.2	−1.0	−7.0	10.0	9.1	0.4	0.4	9.2	11.1	3.2	−5.1	26.0	26.5	4.4	−4.8	14.7	16.1	2.3	−3.7
Pernambuco	14.4	17.7	−1.4	−1.9	16.6	16.2	0.4	0.1	3.0	9.1	0.0	−6.1	12.5	11.1	−1.3	2.7	18.0	26.5	−3.0	−5.5	12.9	16.1	−1.1	−2.1

Rio Grande do Sul	10.7	17.7	−0.8	−6.3	17.3	16.2	−0.7	1.8	6.2	9.1	−0.9	−2.0	8.4	11.1	−1.0	−1.7	17.6	26.5	−0.8	−8.1	12.0	16.1	−0.8	−3.2
Paraná	8.0	17.7	−3.1	−6.7	12.9	16.2	0.2	−3.4	8.9	9.1	−0.5	0.3	7.7	11.1	−0.9	−2.5	21.8	26.5	−0.5	−4.2	11.8	16.1	−1.0	−3.3
Rio de Janeiro	13.6	17.7	5.0	−9.1	8.1	16.2	2.1	−10.2	5.2	9.1	3.2	−7.1	5.1	11.1	5.2	−11.2	22.5	26.5	3.3	−7.3	10.9	16.1	3.8	−9.0

[a]Ranked in terms of 5-period average employment growth rate (from highest to lowest)

The ranking is consistent with long-run regional convergence. The observed employment growth differentials are the result of a reduction in concentration of economic activities that essentially benefited the Center-West and North Brazil, rather than the traditional large markets of São Paulo and Rio de Janeiro.[5] This can be seen from two features in Table 7.2. First, the top ten states in terms of total employment growth are in all 5-year sub-periods either from the North or Centre-West regions, with a few exceptions that refer to states from the Northeast region, which is in any case contiguous to the north and middle-west regions. Brazil's richest states of São Paulo and Rio de Janeiro occupied the lower end of the employment growth ranking. These two states were 23rd and 27th respectively in terms of the five-period averages from 1981 to 2006.

Table 7.3 shows state by industry Location Quotients (hereafter LQ). Using our previous notation, these are defined as follows: $LQ_{ir}^{t} = \frac{\left(E_{ir}^{t}/E_{0r}^{t}\right)}{\left(E_{i0}^{t}/E_{00}^{t}\right)}$. LQ $<$ 1 indicates that the area is less specialized than the nation in a particular sector; LQ $>$ 1 means the area is more specialized than the nation in a specific sector. Based on Tables 7.2 and 7.3, three main questions are addressed.

The first question is to identify the states that have a high competitive growth rate (Table 7.2) and to check how this is linked to the LQ (Table 7.3). North and Center-West states occupy the top nine positions in competitiveness (as proxied by shift-share analysis). Their generally positive competitive effect suggests that their sectoral employment grew generally above national sectoral employment.[6] Specifically, the behavior of the competitive effect in the last sub-period (2001–2006) is consistent with successful policies to control inflation, reduce unemployment and liberalize trade. Moreover, stabilization policies – when implemented – have benefited the North and Center-West states rather more than the whole nation. This result may be interpreted as positive as it shows a process of employment deconcentration across states.

The analysis of the LQs in Table 7.3 indicates that the most competitive states, due to overrepresentation (signaled by an LQ higher than 1.5) of national growth industries, are basically located in the North and Center-West regions. However, being historically lagging regions, the development of infrastructure there helped boost employment in all sectors over the study period. On the other hand, the northern states were less specialized on average. Table 7.3 shows that they had relatively low Hirschman-Herfindahl Indexes in 1981.

[5] Chahad et al. (2002) found a similar result when analysing employment change from 1985 to 1997 in Brazil. However, such findings contradict previous studies for the period 1960–1970 in which centripetal forces were apparently stronger than centrifugal forces, with high growth of the number of firms, the number of people employed, and gross value of production in the main metropolitan centres (Sao Paulo and Rio de Janeiro or former Guanabara) (Enders 1980).

[6] Table 7.3 shows that these states have high location quotients in 1981 for those sectors that had relatively high subsequent growth (such as commerce, electricity, gas and water, mining and transport and communications).

Table 7.3 Location quotients and Hirschman-Herfindahl index of Brazil's states, 1981

State	Agriculture and fishing	Commerce	Construction	Electricity, water and gas	Financial sector	Manufacturing	Mining	Services	Transportation and communication	Hirschman-Herfindahl index (HHI)
Acre	*0.400*	**1.571**	*0.468*	**2.156**	**1.619**	0.809	1.170	**1.599**	**1.819**	0.227
Amazonas	*0.296*	**1.797**	1.020	**2.021**	1.019	1.453	1.255	1.161	1.381	0.194
Amapá	*0.191*	**1.598**	1.481	1.308	0.741	0.830	**2.674**	**1.516**	**2.042**	0.216
Pará	*0.409*	**1.803**	1.049	1.301	0.867	0.792	**2.774**	1.345	**1.789**	0.198
Rondônia	*0.445*	**1.911**	1.149	**1.800**	0.603	0.754	**3.184**	1.202	**1.969**	0.186
Roraima	*0.239*	**1.544**	**2.328**	**3.701**	1.384	*0.373*	**8.416**	1.282	**1.576**	0.188
Tocantins	**2.351**	**1.756**	0.194	*0.179*	*0.003*	*0.010*	*0.040*	*0.023*	*0.444*	0.614
Alagoas	**1.712**	0.625	0.873	*0.486*	*0.390*	0.569	0.843	0.683	0.670	0.353
Bahia	**1.710**	0.841	0.757	0.811	0.513	*0.446*	1.426	0.674	0.656	0.351
Ceará	1.013	0.889	**2.104**	0.763	*0.399*	0.934	0.537	0.821	0.619	0.213
Maranhão	**2.086**	0.628	0.594	0.740	*0.229*	*0.227*	1.006	0.535	0.511	0.479
Paraíba	1.043	0.964	**2.477**	0.847	*0.438*	*0.477*	1.294	0.861	0.725	0.223
Pernambuco	1.230	1.157	0.936	1.079	0.619	0.764	*0.334*	0.858	0.919	0.241
Piauí	**1.629**	0.585	**2.209**	*0.486*	*0.340*	*0.247*	*0.494*	0.575	0.542	0.339
Rio Grande do Norte	1.077	0.908	1.320	1.033	0.629	0.613	**5.410**	1.009	0.945	0.218
Sergipe	1.358	0.651	1.140	0.929	*0.426*	0.606	**6.714**	0.776	1.166	0.256
Distrito Federal	*0.113*	**1.583**	1.219	**1.983**	**2.658**	*0.432*	*0.053*	**1.899**	**1.740**	0.276
Goiás	1.179	1.055	0.902	0.833	0.864	*0.453*	**1.681**	1.132	0.937	0.249
Mato Grosso do Sul	1.012	1.113	1.173	1.146	0.790	0.597	0.689	1.110	1.205	0.219
Mato Grosso	1.327	1.087	0.885	1.337	0.859	*0.362*	**5.546**	0.853	1.088	0.255

(continued)

Table 7.3 (continued)

State	Agriculture and fishing	Commerce	Construction	Electricity, water and gas	Financial sector	Manufacturing	Mining	Services	Transportation and communication	Hirschman-Herfindahl index (HHI)
Espírito Santo	1.417	0.798	0.982	0.669	0.732	0.656	**1.511**	0.793	0.985	0.275
Minas Gerais	1.190	0.833	0.964	0.809	0.745	0.689	1.110	1.075	0.925	0.246
Rio de Janeiro	*0.178*	1.227	1.181	**1.633**	**1.714**	1.229	0.747	**1.569**	**1.704**	0.225
São Paulo	*0.371*	1.167	0.917	1.006	**1.679**	**1.864**	*0.365*	1.168	1.130	0.207
Paraná	**1.551**	0.917	0.686	0.803	0.802	0.573	*0.491*	0.761	0.825	0.309
Santa Catarina	1.402	0.730	0.546	1.485	0.645	1.174	1.165	0.676	0.897	0.276
Rio Grande do Sul	1.190	0.894	0.797	0.994	0.872	0.983	1.128	0.909	0.889	0.237

Notes: States are ordered from north to south. Location quotients higher than 1.5 are given in bold, and those lower than 0.5 are in italics

The Hirschman-Herfindahl index is defined as $HHI_r^t = \sum_i \left(E_{ir}^t / E_{i0}^t\right)^2$ with E_{ir}^t employment in sector i in region r at time t

Considering the first sub-period (1981–1986), there are five sectors (out of nine) that grew fast with a growth rate of at least 20 % nationally. North and Center-West states have a LQ greater than 1.5 in three of these sectors, such as commerce, mining and services. On the other hand, São Paulo and Rio de Janeiro accounted for most national employment in the financial sector and manufacturing. These two sectors, however, experienced weak growth between the second and fourth sub-periods (in the third sub-period both even had negative growth rates) before they recovered in the last sub-period due to successful policies implemented in this sub-period.

The second question is whether the observed total regional employment growth rates in Table 7.2 are consistent with the earlier described economic history of Brazil. Table 7.2 indicates that, as expected, the core regions of Southeast and South had generally lower employment growth rates than the lagging North and Center-West and some Northeast states. This trend is compatible with high specialization of the lagging regions in three (out of five) of the faster growing sectors of economic activity in Brazil.[7]

The third issue is whether the differences in total state employment growth rates are due to differences in industry-mix at the state level relative to the national economy or whether these differences are due to the competitive advantage that a specific state has relative to the national economy. Table 7.2 shows that the top six (out of 27) states – in terms of the five-period average employment growth rates – are the only states that have had a positive industry-mix effect in all 5-year periods.[8] Again, these states are either from the North or the Center-West regions of Brazil and appear to have had an industry structure that has been more beneficial than that of the other states, even during periods in which, for some sectors, the nation's sectoral growth rate was less than average growth. Additionally, these top six states had the highest competitive effect over time as a result of a high LQ in six (out of nine) sectors in 1981 (see Table 7.3) and specialization in sectors with a growth rate larger than that observed for the nation.

Conversely, 16 of the other states had a negative five-period average industry-mix growth rate. This finding indicates that these 16 states were harmed by poor national performance through following the nation's trend in the sub-periods in which the nation had a negative (or low positive) sectoral employment growth rates, because they were endowed with industries that were growing less than average. It is not a surprise that those 16 states also had the smallest (even negative) average competitive effect over the study period.

[7] Three sectors in which North and Center-West states had a comparative disadvantage are agriculture and fishing, manufacturing, and the financial sector. These latter two sectors had some of the highest growth rates in the sub-period 2001–2006, 127.5 % and 38.6 %, respectively (see Table 7.1).

[8] With the exception of Rio de Janeiro which also had a positive industry-mix effect in all of the 5-year periods, but the lowest five-period average total employment growth due to a consistently high negative competitive effect.

7.5 Structural Change

This section investigates whether the states' sectoral growth rates followed the national trend. The approach to answer this question is to decompose the industry-mix effect from Eq. (7.6) in Sect. 7.2 as follows (see also Cochrane and Poot 2008):

$$\sum_i s_{ir}^{t-1}\left(g_{i0}^t - g_{00}^t\right) \equiv \sum_i s_{ir}^t\left(g_{i0}^t - g_{00}^t\right) + \sum_i \left(s_{ir}^{t-1} - s_{ir}^t\right)\left(g_{i0}^t - g_{00}^t\right) \tag{7.7}$$

The second term of the right-hand side of the equation above measures the effect of changing industry composition on the regional employment growth rate. This will be referred to as the structural change effect. The industry-mix effect calculated by means of end-of-the period weights will be referred to as the modified industry-mix effect.

The states among the top ten in terms of the total employment growth rate (see Table 7.2) also have the highest (positive) modified industry-mix effects on average (Table 7.4). These states are: Acre, Amazonas, Amapá, Pará, Rondônia, and Roraima from the North region and Distrito Federal, Goiás, and Mato Grosso do Sul from the Center-West region. However, Rio de Janeiro and São Paulo have modified industry-mix effects at levels comparable to those of North and Center-West states.

The structural effect is negative in all but eight cases, which refer to states in the North or Northeast. This indicates that the regional sectoral trends in those cases were different from the national sectoral trends in the specified periods. However, given that the number of these cases is small, the overall conclusion is that most states have generally not gone against the national trend in terms of structural change. Hence, when a sector grows faster (slower) than average, its share in employment increases (decreases) in almost all regions. The positive structural change effects occur predominantly in the fourth and fifth 5-year periods.

7.6 Alternative Formulations

One of the criticisms of classic shift-share analysis is that the industry-mix effect interacts with the competitive effect. In other words, it is difficult from the shift-share identity to isolate regional performance that truly depends on a region's strengths because a region can grow faster either as a result of an 'appropriate' mix of industries that are also doing well elsewhere, or as a consequence of being specialized (i.e. a high LQ) in a buoyant industry which is not found elsewhere. This section reviews and applies some of the shift-share extensions that were done to isolate the interaction between the industry-mix and competitive effects in a region's growth (Loveridge and Selting 1998, pp. 43–49; Cochrane and Poot 2008).

The first extension considered is the calculation of Esteban-Marquillas homothetic employment, which is the employment that a region r would have

Table 7.4 The modified industry-mix and structural change effects on employment growth in Brazil

	Modified industry-mix effect					Structural change effect				
State	1981–1986	1986–1991	1991–1996	1996–2001	2001–2006	1981–1986	1986–1991	1991–1996	1996–2001	2001–2006
Acre	6.91	4.48	4.80	3.05	−2.82	−1.43	−0.09	−1.01	1.90	2.81
Amazonas	5.13	1.67	2.63	4.25	0.83	−0.31	−1.74	−1.14	−0.84	2.15
Amapá	6.06	4.88	4.02	6.27	1.58	−1.82	0.20	0.85	−2.62	0.80
Pará	5.05	3.77	3.30	3.68	1.93	−1.03	−0.82	−0.68	−0.71	0.15
Rondônia	4.88	3.55	2.64	3.27	−2.40	−1.63	−0.64	−0.26	0.65	3.40
Roraima	5.65	3.43	4.98	4.03	−1.45	−4.00	−0.25	−2.28	0.93	1.42
Tocantins	−6.93	−0.20	0.67	−2.01	−2.02	−0.27	0.46	−4.63	−1.17	−2.72
Alagoas	−4.00	0.30	−0.65	−4.12	−3.97	−0.60	−1.26	−0.79	0.55	−1.55
Bahia	−3.44	0.75	−0.46	−2.78	−2.89	−0.78	−0.81	−0.67	−1.01	−1.57
Ceará	−0.34	0.73	−0.41	−1.22	−0.43	−2.65	−1.18	−0.16	−2.12	−1.46
Maranhão	−5.23	0.05	−1.75	−4.71	−3.83	−1.20	−0.86	−0.72	−2.00	−2.18
Paraíba	−1.00	1.45	0.30	−1.02	−1.44	−3.24	−0.20	−0.56	−2.02	−1.55
Pernambuco	0.27	1.32	0.90	−1.20	−0.45	−1.72	−0.97	−0.89	−0.14	−2.57
Piauí	−4.57	0.28	−0.86	−4.53	−4.39	−3.23	−0.97	−0.87	−0.14	−1.26
Rio Grande do Norte	0.47	1.43	0.87	0.46	0.51	−1.51	−0.86	−0.66	−1.03	−1.91
Sergipe	−1.74	0.77	0.82	−0.32	0.37	−1.05	−1.48	−1.68	−0.89	−2.55
Distrito Federal	6.66	4.74	5.06	6.21	5.99	−1.18	−0.67	−0.52	−1.14	−1.85
Goiás	0.89	2.08	2.09	2.52	2.09	−1.61	−0.72	−1.18	−2.05	−2.05
Mato Grosso do Sul	0.62	2.53	2.13	1.71	1.12	−1.24	−0.63	−0.65	−2.29	−1.48
Mato Grosso	0.16	0.86	0.23	−1.08	−0.89	−1.99	−1.23	−1.95	−0.62	−1.16
Espírito Santo	−1.23	0.69	0.37	−0.32	1.61	−1.73	−0.96	−1.14	−0.80	−3.15
Minas Gerais	0.26	0.84	0.94	0.13	0.62	−1.35	−0.38	−1.12	−0.62	−1.97
Rio de Janeiro	6.07	3.09	4.35	5.98	5.85	−1.04	−0.95	−1.18	−0.81	−2.57
São Paulo	5.49	0.17	1.78	4.15	6.71	−0.91	−1.20	−1.36	−0.98	−2.34
Paraná	−1.17	0.76	0.56	0.23	2.81	−1.88	−0.59	−1.08	−1.18	−3.31
Santa Catarina	−0.63	−1.49	−1.29	−0.06	2.50	−1.17	−0.69	−1.26	−1.94	−1.12
Rio Grande do Sul	1.07	0.10	−0.16	−0.45	1.32	−1.83	−0.82	−0.79	−0.60	−2.09

Notes: The states are ordered from north to south had in industry i if the share of industry i in regional employment was the same as the share of industry i in national employment:

$$EH_{ir}^{t-1} = \frac{E_{i0}^{t-1} E_{0r}^{t-1}}{E_{00}^{t-1}} \tag{7.8}$$

Hence, homothetic employment would be the same as actual employment if, and only if, LQ $=$ 1. The decomposition of competitive effect using Eq. (7.8) is:

$$\begin{aligned} CE_{ir}^{t} &\equiv CEH_{ir}^{t} + AE_{ir}^{t} \\ &\equiv \left(g_{ir}^{t} - g_{i0}^{t}\right) \times EH_{ir}^{t-1} + \left(g_{ir}^{t} - g_{i0}^{t}\right) \times \left(E_{ir}^{t-1} - EH_{ir}^{t-1}\right) \end{aligned} \tag{7.9}$$

CEH_{ij}^{t} measures the comparative advantage of region's sector i compared to the nation ($g_{ir}^{t} > g_{i0}^{t}$) and AE is the Esteban-Marquillas' allocative effect which depends on the extent to which the region r is specialized in the industry i (i.e. homothetic employment differs from actual employment).

The Esteban-Marquillas' extension can also be applied to the industry-mix effect. This is referred to as Esteban-Marquillas' second decomposition,

$$E_{ir}^{t} - E_{ir}^{t-1} \equiv \Delta E_{ir}^{t} \equiv NEEM2_{ir}^{t} + IMEM2_{ir}^{t} + CEH_{ir}^{t} + AE_{ir}^{t} \tag{7.10}$$

$$NEEM2_{ir}^{t} = g_{i0}^{t} \times EH_{ir}^{t-1} \tag{7.11}$$

$$IMEM2_{ir}^{t} = g_{i0}^{t} \times \left(E_{ir}^{t-1} - EH_{ir}^{t-1}\right) \tag{7.12}$$

CEH_{ir}^{t} and AE_{ir}^{t} are defined as in (7.9); $NEEM2_{ir}^{t}$ is the Esteban-Marquillas modified national growth effect on industry i in the r^{th} region between times ($t-1$) and t, and $IMEM2_{ir}^{t}$ is the Esteban-Marquillas modified industry-mix effect on industry i in the r^{th} region between times ($t-1$) and t.

Keil (1992) showed that:

$$\sum_i NEEM_{ir}^{t} = \sum_i NE_{ir}^{t} \text{ and } \sum_i IMEM2_{ir}^{t} = \sum_i IM_{ir}^{t} \tag{7.13}$$

We can see that CEH_{ir}^{t} and CE_{ir}^{t} are closely linked via the location quotient LQ_{ir}^{t} as follows:

$$CEH_{ir}^{t} = \frac{CE_{ir}^{t}}{LQ_{ir}^{t}} \tag{7.14}$$

in which the location quotient LQ_{ir}^{t} is defined as before (and reported for 1981 in Table 7.3). Other authors also use homothetic employment in their extensions.

Based on Eqs. (7.2) and (7.3), Bishop and Simpson (1972) created alternative expressions for national growth and industry-mix effects:

$$\Delta E_{ir}^{t} = E_{ir}^{t} - E_{ir}^{t-1} \equiv NEBIS_{ir}^{t} + IMBIS_{ir}^{t} + CE_{ir}^{t} \tag{7.15}$$

$$NEBIS_{ir}^{t} \equiv g_{00}^{t} \times E_{ir}^{t-1} + (g_{i0}^{t} - g_{00}^{t}) \times EH_{ir}^{t-1} \tag{7.16}$$

$$IMBIS_{ir}^{t} = \left(g_{i0}^{t} - g_{00}^{t}\right) \times (E_{ir}^{t-1} - EH_{ir}^{t-1}) \tag{7.17}$$

The new components of the three equations above are:

$NEBIS_{ir}^{t}$ = the Bishop-Simpson modified national growth effect on industry i in the r^{th} region between $(t-1)$ and t;

$IMBIS_{ir}^{t}$ = the Bishop-Simpson modified industry-mix effect on industry i in the r^{th} region between $(t-1)$ and t.

We tested the relationship between different measures introduced above by Pearson correlation coefficients for each period and each measure for the 27 States with nine industries, i.e. 243 observations per period. The results are given in Table 7.5. *IM* is highly correlated with *IMBIS* and *IMEM2*, except for the 2001–2006 period in there is no correlation between *IM* and *IMEM2*; *CE* is highly correlated with *CEH*; *NEBIS* is highly correlated with *NEEM2*. *IM* and *CE* have a relatively low or insignificant correlation. These results are qualitatively similar to those found by Cochrane and Poot (2008) for New Zealand. However, even more of the 28 correlation coefficients per period are statistically significant (positive or negative) in the Brazilian case than in the New Zealand case.

It is also useful to consider a comparison between the findings in this chapter and those of Loveridge and Selting (1998, p. 52). However, Loveridge and Selting calculated the shift-share component extensions for Minnesota from 1979 to 1988 by using income rather than employment. They also calculated correlations for just the entire study period, rather than for sub-periods. Therefore, Loveridge and Selting's (1998) results are verified here for each sub-period by considering only significant correlations in both studies. Identical results in both studies are: *AE* and *CEH*: the correlation is approximately -1; *IMBIS* and *IM*: positive correlation; *NEEM2* and *IM*: generally positive correlation; *IMEM2* and *IM*: a significant positive correction, except the last sub-period; *NEBIS* and *IM*: generally positive correlation; *NEBIS* and *CE*: positive correlation, and in the Brazilian case the correlation is very high; *NEBIS* and *NEEM2*: positive correlation of around 0.9; *IMBIS* and *NEEM2*: generally positive correlation; *IMBIS* and *IMEM2*: generally identical positive correlation of 0.8.

In general, we can conclude that while the extensions are theoretically attractive, in practice the information contained in the alternative measures can often be proxied by the basic, and easily interpretable, measures. The cross-study comparison shows that this is the case for the Brazilian, US and New Zealand data. However, as we will show in the next two sections, extensions that introduce a spatial dimension add an important and informative component to shift-share analysis.

Table 7.5 Simple correlations between shift-share components for the 27 States of Brazil

	IM	*CE*	*CEH*	*AE*	*NEBIS*	*IMBIS*	*NEEM2*	*IMEM2*
1981–1986								
IM	1							
CE	**0.510**	1						
CEH	**0.436**	**0.965**	1					
AE	−0.287	−**0.806**	−**0.934**	1				
NEBIS	**0.583**	**0.990**	**0.943**	−**0.770**	1			
IMBIS	**0.998**	*0.455*	*0.381*	−**0.237**	**0.532**	1		
NEEM2	**0.587**	**0.996**	**0.955**	−**0.790**	**0.994**	**0.535**	1	
IMEM2	**0.519**	*−0.471*	−**0.512**	**0.508**	*−0.386*	**0.571**	*−0.388*	1
1986–1991								
	IM	*CE*	*CEH*	*AE*	*NEBIS*	*IMBIS*	*NEEM2*	*IMEM2*
IM	1							
CE	*0.418*	1						
CEH	**0.566**	**0.660**	1					
AE	−**0.549**	−**0.525**	−**0.986**	1				
NEBIS	*0.468*	**0.929**	**0.714**	−**0.603**	1			
IMBIS	**0.999**	*0.387*	**0.554**	−**0.541**	*0.439*	1		
NEEM2	**0.519**	**0.993**	**0.687**	−**0.558**	**0.930**	**0.490**	1	
IMEM2	**0.762**	−0.270	0.131	−0.208	−0.168	**0.783**	−0.158	1
1991–1996								
	IM	*CE*	*CEH*	*AE*	*NEBIS*	*IMBIS*	*NEEM2*	*IMEM2*
IM	1							
CE	−0.012	1						
CEH	−0.378	**0.682**	1					
AE	*0.381*	−**0.676**	−**1.000**	1				
NEBIS	0.054	**0.974**	**0.615**	−**0.609**	1			
IMBIS	**0.998**	−0.067	*−0.416*	*0.419*	0.002	1		
NEEM2	0.070	**0.996**	**0.646**	−**0.640**	**0.975**	0.015	1	
IMEM2	**0.857**	−**0.525**	−**0.673**	**0.672**	*−0.454*	**0.884**	*−0.453*	1
1996–2001								
	IM	*CE*	*CEH*	*AE*	*NEBIS*	*IMBIS*	*NEEM2*	*IMEM2*
IM	1							
CE	0.231	1						
CEH	0.330	**0.833**	1					
AE	−0.322	*−0.421*	−**0.853**	1				
NEBIS	**0.613**	**0.816**	**0.687**	−0.356	1			
IMBIS	**0.999**	0.219	0.321	−0.320	**0.605**	1		
NEEM2	*0.467*	**0.968**	**0.845**	*−0.471*	**0.899**	*0.455*	1	
IMEM2	**0.977**	0.019	0.157	−**0.239**	*0.454*	**0.980**	0.268	1
2001–2006								
	IM	*CE*	*CEH*	*AE*	*NEBIS*	*IMBIS*	*NEEM2*	*IMEM2*
IM	1							
CE	0.365	1						
CEH	0.348	**0.985**	1					

(continued)

Table 7.5 (continued)

	IM	*CE*	*CEH*	*AE*	*NEBIS*	*IMBIS*	*NEEM2*	*IMEM2*
AE	−0.324	−**0.947**	−**0.989**	1				
NEBIS	*0.420*	**0.995**	**0.979**	−**0.942**	1			
IMBIS	**0.994**	0.259	0.241	−0.221	0.316	1		
NEEM2	*0.437*	**0.997**	**0.980**	−**0.942**	**0.996**	0.334	1	
IMEM2	0.178	−**0.851**	−**0.845**	**0.819**	−**0.814**	0.288	−**0.807**	1

Notes: Bold – Significant at 1 % level (2 tailed); Italics – Significant at 5 % level (2 tailed). Correlation coefficients of absolute value of 0.8 or above are underlined

7.7 Exploratory Spatial Analysis of Shift-Share Components

This section examines the spatial distribution of the industry-mix and competitive effects of the traditional shift-share decomposition. The tools of spatial autocorrelation analysis that are used include Moran's *I* and cluster maps (Getis 1991; Anselin 1995). Spatial autocorrelation is increasingly recognized as a major issue in econometric analysis, because the levels of many socio-economic variables are not random in space. In other words, those levels depend on the geographical location of any given region *r*. It often matters whether region *r* has many neighbors or is relatively isolated (Nazara and Hewings 2004). Researchers who ignore the problem of spatial autocorrelation are more likely to estimate misguided models.

One global (i.e. summary across space) measure of spatial autocorrelation is Moran's *I*, which is defined as follows:

$$I = \frac{\frac{1}{n}\sum_{i=1}^{R}\sum_{r=1}^{R} W_{ir}(z_i - \bar{z})(z_r - \bar{z})}{\sigma^2(z)} \tag{7.18}$$

In this equation z_i is a variable observed at location *i* with $i = 1,\ldots,R$ ($R = 27$ in the application to Brazilian states below), w_{ij} is a spatial weight that portrays interaction between the pairs of regions *i* and *r* (i; $r = 1,\ldots, 27$); $\bar{z}$ is the sample average of z and $\sigma^2(z)$ is the sample variance of z. A matrix of spatial weights can be created by means of software or manually. Moran's *I* autocorrelation measure ranges from -1 to +1. Positive values of Moran's *I* indicate positive spatial correlation, negative values suggest that regions are generally surrounded by regions that are "opposites" (in practice this is rarely observed), and a small or zero Moran's *I* the absence of spatial correlation (software is available to calculate the statistical significance of spatial correlation, which depends on the spatial weights matrix).

The simplest spatial interaction matrix is one in which interaction is determined by contiguity, with "1" in the original matrix indicating contiguity and "0" indicating non-contiguity. To create weights, the matrix is row-standardised (each row element is divided by the row sum).

A geographic evaluation of spatial autocorrelation is achieved by LISA (Local Indicators of Spatial Association) because these indicators allow the researcher to identify "outlier regions". This is illustrated by significance and cluster maps in which values of the variable of interest are geo-coded, and the levels are indicated by color or shading on a map.

A LISA is a statistic that satisfies two criteria (Cochrane and Poot 2008, p. 71; Le Gallo and Kamarianakis 2011, p. 128): (i) the LISA for each observation gives an indication of significant spatial clustering of similar values around that observation; and (ii) the sum of the LISA for all observations is proportional to a global indicator of spatial association.

The local version of Moran's I statistic is a LISA and expressed as follows:

$$I_i = (z_i - \bar{z}) \sum_{j=1}^{R} w_{ij}(z_j - \bar{z}) \tag{7.19}$$

and hence

$$I \equiv \frac{1}{n\sigma^2(z)} \sum_{i=1}^{R} I_i \tag{7.20}$$

The interpretation of Moran's I is facilitated by considering the four quadrants of the scatter plot of the measure of the spatially weighted outcomes in surrounding regions against the value of the variable of interest in the region itself:

> The four different quadrants of the scatterplot correspond to the four types of local spatial association between a region and its neighbours: HH denotes a region with a high value surrounded by regions with high values; LH a region with a low value surrounded by regions with high values, and so on. Quadrants HH and LL (respectively LH and HL) refer to positive (respectively negative) spatial autocorrelation indicating spatial clustering of similar (respectively dissimilar) values (Le Gallo and Kamarianakis 2011, p. 128).[9]

In what follows, Moran's I scatterplots and cluster maps are presented for the Industry-Mix (IM) and Competitive Effect (CE) components of the classic shift share analysis of Sect. 7.4. The chosen values for IM and CE for each of the cluster maps are the pooled observations across the five sub-periods. The spatial weights matrix for Moran's I is a simple first order row-standardized "queen's contiguity" matrix of Brazil that was created in Microsoft Excel. Queen's contiguity means that regions are considered contiguous if they have either a common border or a common edge.[10]

[9] These clusters are known in the spatial econometrics literature as: High-High = hot spots; Low-High = spatial outliers; High-Low = spatial outliers, Low-Low = cold spots. Other areas are those with no significant spatial autocorrelation.

[10] On the other hand, rook contiguity and bishop contiguity consider regions as contiguous if and only if they share a common border and a common edge, respectively.

Moran's *I* scatterplots for both IM and CE were drawn and Moran's *I* was calculated by an OLS regression of the spatially weighted value for all regions outside any particular region against the value of the variable in that particular region. This OLS regression is precisely what is represented by Eq. (7.18), except that the panel structure of the pooled data must additionally be taken into account. The Moran scatter plot for the IM effect is displayed in Fig. 7.2. Moran's *I* (i.e. the slope of the regression line) is positive (0.4563) and statistically significant at the 1 % level. This indicates that there is a clear pattern of positive spatial correlation of the IM effect. The cluster map (Fig. 7.3) shows the hot spots, i.e. those states with high values of the industry mix effect that are surrounded by states with also high levels in industry-mix. They include Amapá, Acre, Distrito Federal and Rio de Janeiro.

On the other hand, there is another cluster of contiguous states with low industry-mix growth rates (cold spots), which are (in south-east and north-northeast land areas): Minas Gerais, Bahia, Tocantins, Sergipe, Alagoas, Pernambuco and Ceará, and (in centre-west and south land area): Mato Grosso do Sul-Paraná.

For the CE effect, the Moran's *I* scatter plot (Fig. 7.4) also shows a positive (0.3375) and statistically significant Moran's *I*. However, comparing Figs. 7.2 and 7.4 it is clear that there is greater spatial correlation in the industry mix effect than in the competitive effect. The cluster map Fig. 7.5 shows various hot spots that are again particularly in the North region.

The economic interpretation of the results above is that two clusters of extremes (High-High *vs.* Low-Low)[11] can be observed, which is consistent with the positive spatial autocorrelation of the shift-share components across states in Brazil generally and the argument that scale economies may arise as a consequence of local agglomeration of economic activities (Krugman 1991). The evidence, based on the two shift-share components, in favour of economic agglomeration theory is as follows: the industry-mix result indicates low specialization for many states.[12] This finding reconfirms many previous studies for Brazil (Rolim 2008; Daumal and Zignago 2010, pp. 747–748, and footnote 22, p. 747) that found convergence across states. However, this convergence is due to the improvement of the industry-mix (i.e. greater diversity) for the less developed middle-west and northern states rather than specialization.

Generally, a high average industry-mix effect indicates that the industrial structure of the fastest growth states has been diversified. On the other hand, the result from Fig. 7.5 clearly shows a higher performance of the northern states which are some of the lagging ones, while the most developed south-eastern states of São Paulo and Rio de Janeiro had a relatively lower competitiveness effect in

[11] This result suggests interstate mobility among businesses may be low.

[12] On the map for industry-mix average, these states are: Amapá, Roraima, Amazonas, Acre, Rondônia, Mato Grosso, Goiás, Distrito Federal, São Paulo, Rio de Janeiro, Rio Grande do Norte, and Paraiba. These states are essentially from north and middle-west which are the regions benefited from convergence from 1981 to 2006.

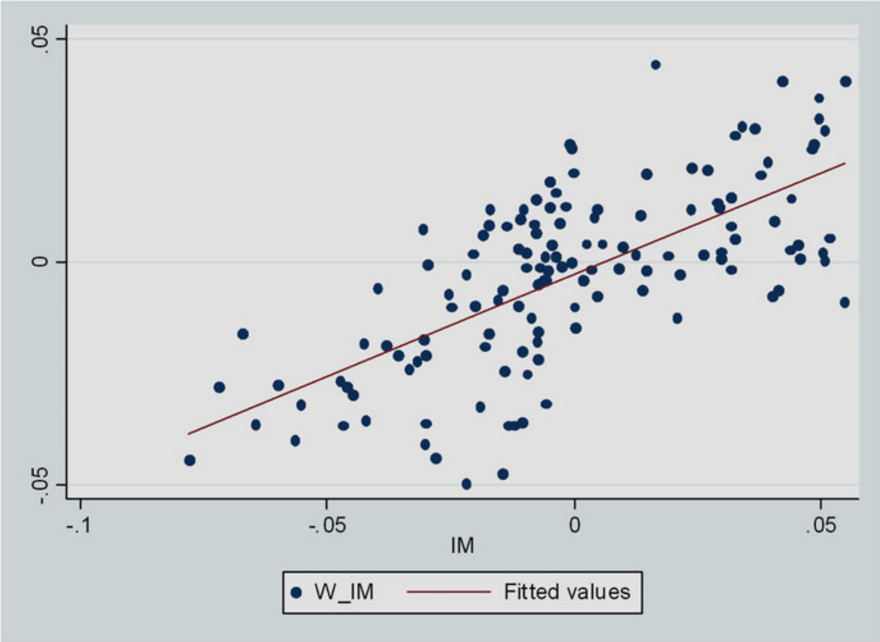

Fig. 7.2 Moran's *I* scatterplot, industry-mix (pooled 5 sub-periods of 5 years)

employment growth. The explanation for higher growth for the lagging regions is as follows. Due to their low income level and their early stage of development, small increases in capital, average education and infrastructure improvement have a large effect on their growth rates. This result supports the neoclassical beta convergence hypothesis (see also Resende 2011 and the references therein).

7.8 Spatial Shift-Share Analysis

While Sect. 7.7 investigated the spatial properties of the classic shift-share components, this section adds a new spatial component to the shift-share accounting framework in order to investigate regional growth of the 27 states in Brazil from 1981 to 2006. The regional growth rate is decomposed according to the taxonomy of spatial shift-share developed by Nazara and Hewings (2004). The growth rate for sector i from time $(t-1)$ to t in region r is linked to the interaction between regions as defined by spatial contiguity. The incorporation of a spatial effect on the growth rate of sector i in region r is done by means of a four step procedure. First, the spatial contiguity matrix (27×27) for the 27 states in Brazil that was used in the previous section is used again here. Spatial contiguity is indicated by "1" if states

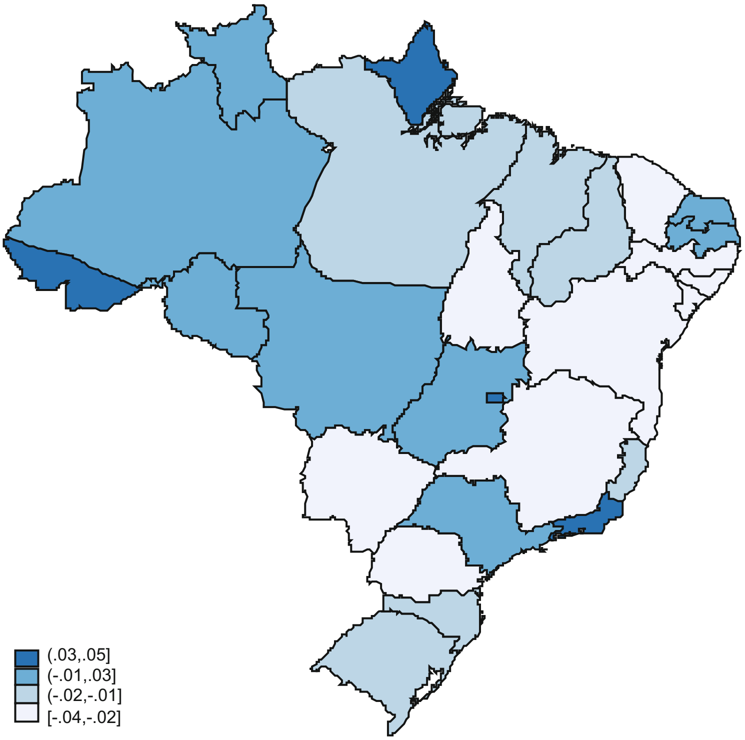

Fig. 7.3 Industry-mix cluster map (average of 5 sub-periods of 5 years)

share a border or an edge, or zero otherwise.[13] Secondly, this spatial contiguity matrix is again row-standardized by taking the ratio between each cell and the sum of its matrix row. Thirdly, values of each cell of the row-standardized spatial weights matrix are multiplied by values of the corresponding sector employment in the states. Fourthly, the percentage change of the spatially weighted sectoral employment from time ($t-1$) to t is defined for each region r as its neighboring regions employment growth rate (with nearby regions getting more weight than regions further away). Hence, following Nazara and Hewings (2004) we define the spatially-weighted sectoral growth rate of a region's r neighbors, gS_{ir}^t, as follows:

$$gS_{ir}^t = \frac{\sum_{k=1}^R w_{rk}E_{ik}^t - \sum_{k=1}^R w_{rk}E_{ik}^{t-1}}{\sum_{k=1}^R w_{rk}E_{ik}^{t-1}} \tag{7.21}$$

[13] Hence queen contiguity is again adopted. The Distrito Federal is a region within Goiás state. They are assumed to share a border.

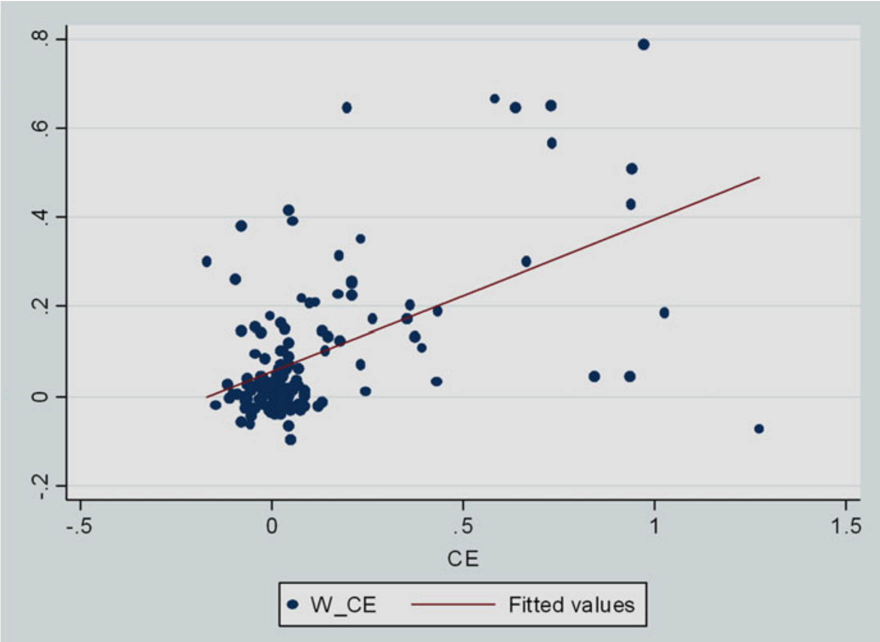

Fig. 7.4 Moran's I scatterplot, competitive-effect (pooled 5 sub-periods of 5 years)

where w_{rk} is the element of row-standardized spatial weights matrix W that captures interactions between regions r and k; E_{ik}^{t-1} and E_{ik}^{t} are, respectively, employment in the i^{th} industry in the k^{th} region at time $(t-1)$ and t.

The decomposition of employment growth rate for sector i from the period $t-1$ to t in the region r after the spatial effects have been incorporated in the classic shift-share method is as follows: substituting Nazara and Hewings (2004, pp. 480–481) Eq. (7.6) in their Eq. (7.5), the following four shift-share components are obtained[14]:

$$\Delta E_{ir}^{t} = (E_{ir}^{t} - E_{ir}^{t-1}) = NE_{ir}^{t} + IM_{ir}^{t} + PSE_{ir}^{t} + LCE_{ir}^{t} \tag{7.22}$$

[14] From Nazara and Hewings (2004, pp. 480–481) seven components can be identified. However, when we aggregate across sectors, two components individually add to zero in each region. These are: neighbor industry-mix effect and regional industry-mix effect (or, the negative own-region industry-mix effect). And there is a double counting for the other two: the neighbor-nation regional shift effect is equal to minus the neighbor-region regional shift effect. Thus, these components are excluded and we can use a simplified version of the spatial shift-share identity with only four components.

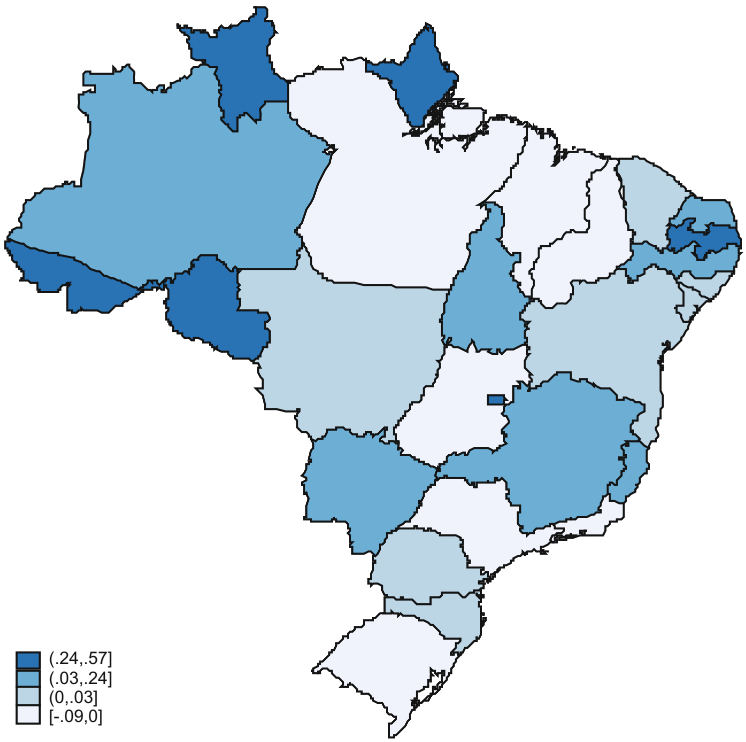

Fig. 7.5 Competitive effect cluster map (average of 5 sub-periods of 5 years)

The first two terms of the right-hand side of Eq. (7.22) are from the classic shift-share method, as defined in Sect. 7.2 (Eqs. 7.2 and 7.3). The new terms that refer to spatial effects for growth of sectors in regions are:

$$PSE_{ir}^{t} = \left(gS_{ir}^{t} - g_{i0}^{t}\right) E_{ir}^{t-1} \tag{7.23}$$

$$LCE_{ir}^{t} = \left(g_{ir}^{t} - gS_{ir}^{t}\right) E_{ir}^{t-1} \tag{7.24}$$

Regional aggregates can be calculated similar to Eq. (7.6) for the industry-mix growth component in the classic shift-share analysis. The interpretation of the two new terms is as follows. PSE_{ir}^{t} may be referred to as the Potential Spatial Spillover Effect. It is the sectoral growth region's sector would have if growth in that sector in surrounding regions spills over to the considered region. This potential spillover effect is adjusted for the national growth rate in that sector, g_{i0}^{t}. The potential spillover effects is only generating an actual spillover effect when spatial autocorrelation in the sector's employment growth is high. The Local Competitive Effect LCE_{ir}^{t} = (or, the negative of neighbour-nation regional shift effect defined by Nazara and Hewings 2004, p. 481) measures the extent to which the industry actually performs better or worse in the considered region than in the surrounding regions.

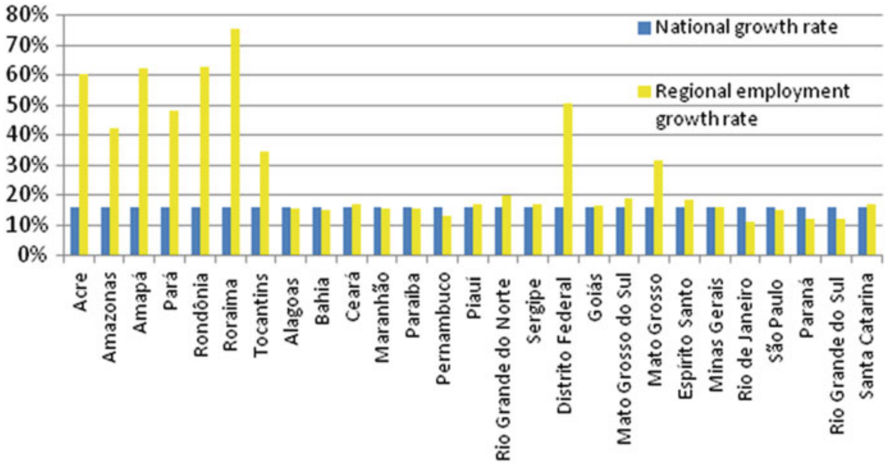

Fig. 7.6 Regional employment growth rates *versus* national growth rate

For clarity we present the results of the spatial shift-share method graphically and compare the average regional growth rates for the five sub-periods with the average for each of the four components (aggregated across the nine sectors). Figure 7.6 compares state growth rates with the national growth rate. Three groups of states stand out. The first group grew faster than the nation and had the highest average growth rates. This group includes: Roraima, Rondônia, Amapá, Acre, Distrito Federal, Pará, Amazonas, Tocantins, Mato Grosso, Rio Grande do Norte, Mato Grosso do Sul, and Espírito Santo. The second group had very similar growth rates to the nation. This group consists of Santa Catarina, Alagoas, Minas Gerais, Maranhão, Goiás, Ceará, Sergipe, and Piauí. Finally, the third group includes the remaining seven states which had a growth rate smaller than the national rate.

Figure 7.7 shows the regional growth rate and the national industry-mix effect. The states with the highest growth rates also had a positive national industry-mix effect, i.e. they were endowed with industries that were growing faster than average. These are seven states in the North and Northeast regions, namely Roraima, Rondônia, Amapá, Acre, Distrito Federal, Pará, and Amazonas. Rio de Janeiro and São Paulo are the only non-fast growing states that are also in this group with a positive national industry-mix effect. The other states yielded a zero or negative industry-mix component. However, the industry-mix effect is small relative to regional growth performance in all states.

Figure 7.8 compares regional growth rates with the potential spatial spillover effect. Most of the states that grew fastest are also those that had the highest (positive) potential spatial spillover effect, i.e. their neighboring states generally grew faster than the expected growth based on industry composition.[15] These are (ordered according to the size of spatial spillover effect, with a cut-off at 15 %):

[15] Excluding Maranhão.

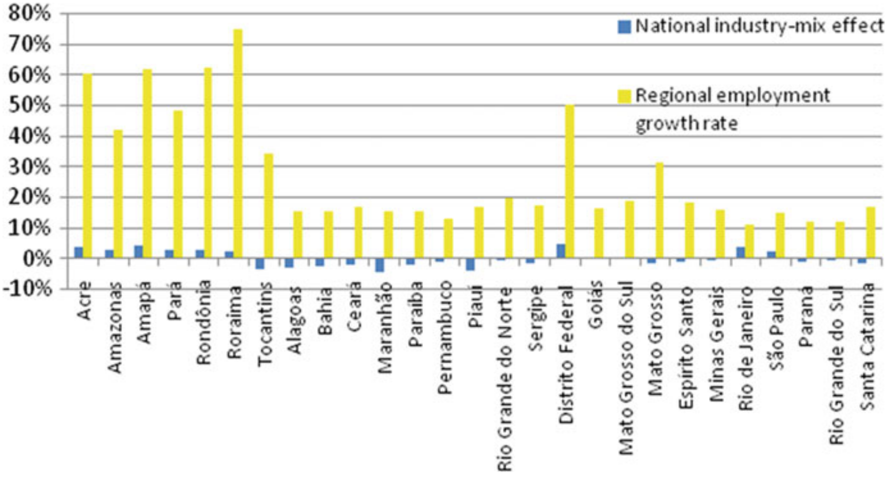

Fig. 7.7 Regional employment growth rates *versus* national industry-mix effect

Amapá, Acre, Roraima, Amazonas, Maranhão, Rondônia, and Mato Grosso. Other states had a smaller positive potential spatial spillover effect or a negative effect, indicating that they were surrounded by states with weak growth relative to the expected growth according to their industry composition. Distrito Federal, São Paulo and Rio de Janeiro had the lowest level of this effect.

Finally, Fig. 7.9 shows the regional growth rate and the local competitive effect. Most of the states that grew fastest also had the highest (positive) local competitive effect, i.e. they grew faster than the surrounding regions. These are (ordered according to the size of local competitive effect, with a cut-off of 13 %): Distrito Federal, Roraima, Rondônia, Pará, Tocantins, Amapá, and Acre. For the states with a negative competitive effect (with Maranhão having the most negative local competitive effect), the poor performance is particularly due to the states' internal weaknesses.

Inspection of the sub-periods indicated that the sub-period 1991–1996 was atypical. Only four states grew fast, namely Tocantins, Amapá, Roraima, and Maranhão, and among the other states, most had a moderate growth rate, between 8 % and 16 %. The characteristics for this period are that it had the lowest national growth rate and very low levels for the other three components, national industry-mix effect, potential spatial spillover effect, and local competitive effect for almost all states. On the other hand, the sub-period 1996–2001 stands out as the one with very negative local competitive effect for nine states, mostly located in the north and northeast regions.

A valid question in spatial shift-share analysis is whether the results are sensitive to the definition of the spatial weights matrix. In order to investigate this issue, an alternative spatial weights matrix was also considered. This alternative row-standardized spatial weights matrix takes into account population data and distance data for the beginning year of each of the five sub-periods. Population data

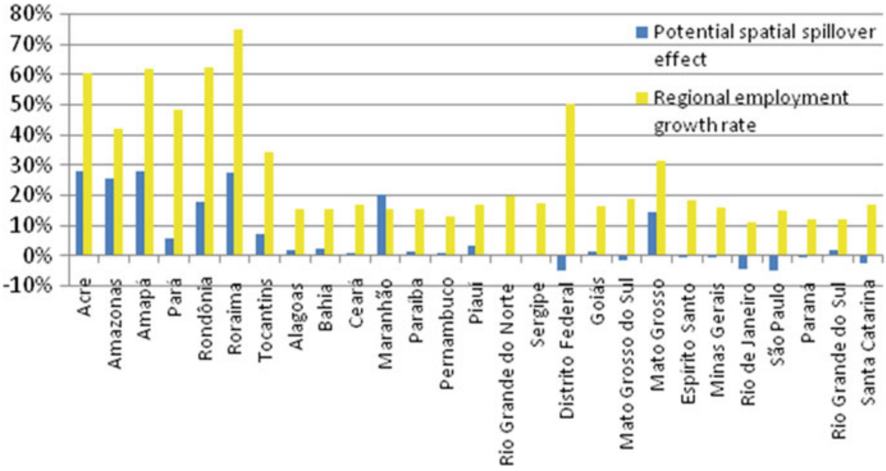

Fig. 7.8 Regional employment growth rates *versus* potential spatial spillover effect

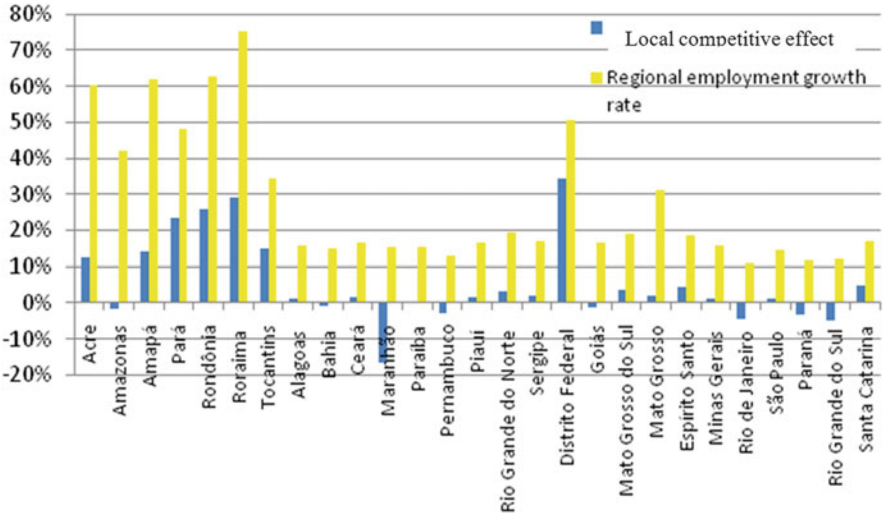

Fig. 7.9 Regional employment growth rates *versus* local competitive effect

used refer to the 27 urban areas that constitute Brazilian state capitals. These urban areas were defined through observation of contiguous municipalities taken together in 2008.

The Municipality Population Data used for construction of the urban areas were obtained from the Institute of Applied Economic Research (IPEA) and the Brazilian Institute of Geography and Statistics (IBGE). We obtained the matrix of distances between the 27 Brazilian state capitals from Brazil's Ministry of Transportation.

The spatial weights matrix used to measure the states' interactions is based on the gravity model, which relates distance between regions and population size of those regions (see Getis 1991, pp. 29–30; Bavaud 1998, pp. 157–158; Brakman et al. 2001, pp. 265–270), and is defined as: [16]

$$w_{rk}^{*(t-1)} = \sqrt{P_r^{t-1} P_k^{t-1}} / D_{rk} \tag{7.25}$$

$$w_{rk}^{t-1} = w_{rk}^{*(t-1)} / \sum_k w_{rk}^{*(t-1)} \tag{7.26}$$

where D_{rk} is distance between states r and k; P_r^{t-1} and P_k^{t-1} are population sizes of the capitals of states r and k respectively at time $(t-1)$, which is the initial year of sub-period under consideration.

Comparing the obtained results using this alternative spatial weights matrix with those above that used the queen contiguity matrix of spatial weights, it turns out that the results are very similar for all components in all states for each of the 5-year sub-periods from 1981 to 2006 as well as for the averages for whole period.[17] Therefore, in the Brazilian context, the first-order spatial weights queen contiguity matrix and the spatial matrix based on the gravity model can substitute for each other because both yield the same results.

7.9 Conclusion

This chapter applied different techniques to analyze employment growth across 27 states in Brazil from 1981 to 2006. Three key conclusions can be drawn from the analysis. First, from the classic shift-share method we conclude that higher employment growth rates of the less developed regions are due to these regions' comparative advantage associated with high performance of the industry-mix and competitive effect components irrespective of the national structural change. This evidence is consistent with studies that found regional convergence in Brazil (Rolim 2008; Daumal and Zignago 2010). Our analysis suggests that one reason for this convergence appears to be an improvement of diversity of the economies of the less developed regions (i.e. northern states) given that they had the generally smallest Hirschman-Herfindahl Indexes as well as higher performance in the industry-mix component. Secondly, examination of the industry-mix and competitive effect components employing ESDA provided evidence of a positive spatial

[16] In fact, the gravity equation suggests that the spatial interaction between regions is inversely related to distance between pairs of regions and positively related with the product of economic size of the two respective regions. Here we used population as an indicator of the scale of regional economy.

[17] Graphs are not shown here but are available upon request.

correlation for both components. This result is consistent with the presence of both agglomeration economies and beta convergence (see also Resende 2011, and the references therein), because, compared with the 1960s, nowadays economic activities are slightly less concentrated in the southern and more developed regions of Brazil.

Thirdly, the chapter provided a simplified version of Nazara and Hewings' (2004) spatial shift-share taxonomy from which the role of spatial autocorrelation in regional growth in Brazil could be quantified in a straightforward way. Growth differentials in favor of North and Center-West states are basically associated with their strengths in two regional components of the spatial shift-share, namely the potential spatial spillover effect and the local competitive effect that, together, outweigh the modest performance on national industry-mix effect for those lagging states.

On the other hand, the major agglomerations of Rio de Janeiro and Sao Paulo continue to benefit from specializations in the financial sector, manufacturing, services and transport and communication. This is consistent with the core-periphery framework that highlights the importance of agglomeration forces in Brazil (Brakman et al. 2001). Due to the large regional disparities and large scale of concentration that continues to be in favor of the southeast-south regions (the core), the fast growth of the lagging regions (the periphery) is still of limited importance in terms of the spatial pattern of economic activities, because the initial conditions that strongly favored the core seem to have essentially permanent effects in Brazil. As a consequence, for instance, the observed modest growth rate for São Paulo (the core) still counts, given the scale of this state's economy, for much of the concentration of economic activities, population and income in Brazil.

A caveat of the available data is the high level of aggregation, i.e. the state level. Had employment data been available at the municipality level, rather than at the state level, this would have allowed a spatial regression approach to quantify the various components of regional growth. Given improving data availability in recent years, this could be an avenue for future research.

References

Abreu MP (2008a) The Brazilian economy, 1930–1980. In: Bethell L (ed) The Cambridge history of Latin America, vol IX. Cambridge University Press, Cambridge, UK, pp 283–394

Abreu MP (2008b) The Brazilian economy, 1980–1994. In: Bethell L (ed) The Cambridge history of Latin America, vol IX. Cambridge University Press, Cambridge, UK, pp 395–430

Abreu MP, Werneck RLF (2008) The Brazilian economy, 1994–2004. In: Bethell L (ed) The Cambridge history of Latin America, vol IX. Cambridge University Press, Cambridge, UK, pp 431–454

Anselin L (1995) Local indicators of spatial association – LISA. Geogr Anal 27(2):93–115

Arcelus F (1984) An extension of shift-share analysis. Growth Change 15(1):3–8

Barff RD, Knight PL (1988) Dynamic shift-share analysis. Growth Change 19(2):1–10

Barro RJ, Sala-i-Martin X (2004) Economic growth. MIT Press, Cambridge, MA

Bavaud F (1998) Models for spatial weights: a systematic look. Geogr Anal 30(2):153–171

Berzeg K (1978) The empirical content of shift-share analysis. J Reg Sci 18(3):463–469

Berzeg K (1984) A note on statistical approaches to shift-share analysis. J Reg Sci 24(2):277–285
Bishop KC, Simpson CE (1972) Components of change analysis: problems of alternative approaches to industrial structure. Reg Stud 6(1):59–68
Brakman S, Garretsen H, van Marrewijk C (2001) An introduction to geographical economics: trade, location and growth. Cambridge University Press, Cambridge, UK
Chahad JPZ, Comune AE, Haddad EA (2002) Shifts in regional employment: an application of the Haynes-Dinc model for Brazil. Paper presented at the European regional science association, Dortmund
Cingano F, Schivardi F (2004) Identifying the sources of local productivity growth. J Eur Econ Assoc 2(4):720–744
Cochrane W, Poot J (2008) Forces of change: a dynamic shift-share and spatial analysis of employment change in New Zealand labour market areas. Stud Reg Sci 38(1):51–78
Daumal M, Zignago S (2010) Measure and determinants of border effects of Brazilian states. Pap Reg Sci 89(4):735–758
Dinc M, Haynes KE (1999) Regional efficiency in the manufacturing sector: integrated shift share and data development analysis. Econ Dev Q 13(2):183–199
Dinc M, Haynes K (2005) Productivity, international trade and reference area interactions in shift-share analysis: Some operational notes. Growth Change 36(3):374–394
Dinc M, Haynes K, Qiangsheng L (1998) A comparative evaluation of shift-share models and their extensions. Australasian J Reg Stud 4(2):275–302
Dunn ES (1960) A statistical and analytical technique for regional analysis. Pap Reg Sci Assoc 6(1):97–112
Enders WT (1980) Regional disparities in industrial growth in Brazil. Econ Geogr 56(4):300–310
Esteban-Marquillas JM (1972) A reinterpretation of shift-share analysis. Reg Urban Econ 2(3): 249–255
Fausto B (1999) A concise history of Brazil (trans: Brakel A). Cambridge University Press, Cambridge, UK (Original work published 1998)
Gazel CR, Schwer RK (1998) Growth of international exports among the states: can a modified shift-share analysis explain it? Int Reg Sci Rev 21(2):185–204
Getis A (1991) Spatial interaction and spatial autocorrelation: a cross-product approach. Environ Plann A 23(9):1269–1277
Glaeser EL, Kallal HD, Scheinkman JA, Shleifer A (1992) Growth in cities. J Polit Econ 100(6): 1126–1152
Haynes K, Machunda ZB (1987) Considerations in extending shift-share analysis: note. Growth Change 18(2):69–78
Keil SR (1992) On the value of homotheticity in the shift-share framework. Growth Change 23(4):469–493
Knudsen DC (2000) Shift-share analysis: further examination of models for the description of economic change. Socio-Econ Plan Sci 34(3):177–198
Knudsen DC, Barff R (1991) Shift-share analysis as a linear model. Environ Plann A 23(3): 421–431
Krugman P (1991) Increasing returns and economic geography. J Polit Econ 99(3):483–499
Le Gallo J, Kamarianakis Y (2011) The evolution of regional productivity disparities in the European Union from 1975 to 2002: a combination of shift–share and spatial econometrics. Reg Stud 45(1):123–139
Lobo EML (1996) Brazil since 1889. In: Tenenbaum BA (ed) Encyclopedia of Latin American history and culture. Simon & Schuster Macmillan, New York, pp 424–432
Loveridge S (1995) A practical approach to shift-share analysis. J Community Dev Soc 26(1): 111–124
Loveridge S, Selting AC (1998) A review and comparison of shift-share identities. Int Reg Sci Rev 21(1):37–58
Markusen AR, Noponen H, Driessen K (1991) International trade, productivity, and U.S. regional job growth: a shift-share interpretation. Int Reg Sci Rev 14(1):15–39

Matlaba VJ, Holmes M, McCann P, Poot J (2012) Agglomeration externalities and 1981–2006 regional growth in Brazil. Stud Reg Sci 42(1):145–161

Mayor M, López AJ (2008) Spatial shift-share analysis versus spatial filtering: an application to Spanish employment data. Empirical Econ 34:123–142

McDonough CC, Sihag BS (1991) The incorporation of multiple bases into shift-share analysis. Growth Change 22(1):1–9

Mitchell W, Myers J, Juniper J (2005) Extending shift-share analysis to account for spatial effects: a study using Australian census data. Working Paper #05-19, Centre of Full Employment and Equity, University of Newcastle, Callaghan, Australia

Nazara S, Hewings GJD (2004) Spatial structure and taxonomy decomposition in shift-share analysis. Growth Change 35(4):476–490

Patterson MG (1991) A note on the formulation of a full-analogue regression model of the shift-share method. J Reg Sci 31(2):211–216

Resende GM (2011) Multiple dimensions of regional economic growth: the Brazilian case, 1991–2000. Pap Reg Sci 90(3):629–662

Rolim C (2008) Decomposing the GDP growth of the great Brazilian regions: dynamic shift-share on recent Brazilian economic cycles. Paper presented at congress of the regional science association international, São Paulo

Chapter 8
The Determinants of Regional Disparities in Skill Segregation: Evidence from German Regions

Fabian Böttcher, Annekatrin Niebuhr, Friso Schlitte, and Javier Revilla Diez

8.1 Introduction

Labour markets in most highly developed countries are characterised by increasing inequalities in qualifications-specific employment prospects. Nickel and Bell (1995) for example find that the demand for high-skilled workers is steadily rising, while low-skilled employment is subject to a considerable decline in many countries of the OECD. On the one hand, this might be explained by a growing supply of skills due to the educational expansion in the 1960s and 1970s. On the other hand, it can be argued, that the increasing international division of labour together with technological and organisational change have been leading to a unilateral rise in the demand for high-skilled labour whereas the low-skilled

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F. Böttcher
CIMA Institut für Regionalwirtschaft GmbH, Moocksgang 5, D-30169 Hannover, Germany
e-mail: boettcher@cima.de

A. Niebuhr (✉)
IAB Nord, Regional Research Network of the Institute for Employment Research, Projensdorfer Str. 82, D-24106 Kiel, Germany
e-mail: annekatrin.niebuhr@iab.de

F. Schlitte
Hamburgisches WeltWirtschaftsInstitut HWWI, Heimhuder Str. 71, D-20148 Hamburg, Germany
e-mail: schlitte@hwwi.org

J.R. Diez
Institute of Economic and Cultural Geography, Leibniz University of Hannover, Schneiderberg 50, 30167 Hannover, Germany
e-mail: diez@wigeo.uni-hannover.de

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compete increasingly with workers in low-wages countries (see Wood 1994, 2002). Furthermore, as a consequence of skill-biased technological and organisational changes more and more less qualified workers do not meet the increasing requirements of jobs on the domestic labour market (see Acemoglu 1998, 2002; Lindbeck and Snower 1996; Spitz-Oener 2006). Some authors also find evidence for a polarisation in skill-specific employment. Autor et al. (2003) hypothesise that highly standardised occupations of medium-skilled employees, such as book- and record-keeping, may be displaced more easily by technological innovations, e.g. by computer programmes, than comparatively simple and less standardised jobs, such as cleaning. Further empirical evidence for this hypothesis is provided by Manning (2004) or Goos and Manning (2007) for the UK and Spitz-Oener (2006) for Germany.

One aspect of the qualification specific changes on the labour market that has not received much attention up to now is the segregation by skill in the production process. The qualification-related structural change affects the internal skill structure of employment at the firm level. However, the changes in the skill composition within firms do not merely reflect the general shift to increasing shares of high-skilled workers in overall employment. Different theoretical models suggest that with proceeding economic integration and due to technological and organisational change segregation by skill at the workplace is likely to increase (e.g. Kremer and Maskin 1996; Acemoglu 1999; Duranton 2004). In other words, more and more firms tend to employ predominantly one specific type of qualification. Some companies, such as fast-food or supermarket chains, recruit mainly low-skilled labour, while others tend to employ primarily high-skilled workers, as for instance software or high-tech producers. As a consequence, employees work more often with similarly qualified co-workers and share less frequently a workplace with differently skilled colleagues. Thus, production processes are characterised by an increasing segregation by skill.

According to these models a key determinant for the level of skill segregation is the level and the variety of skills in the labour force available to firms. Since production technologies and skill structures are characterised by pronounced regional disparities, there are likely significant differences in the level of segregation between regions. In particular, there might exist disparities between cities and rural areas. High-skilled workers are to be found more frequently in agglomerated areas because of their specific sector structure as well as urbanisation and localisation advantages (for Germany see Fromhold-Eisebith and Schrattenecker 2006). Therefore, skill segregation could be more pronounced in agglomerated areas.

The composition of skills within firms and the level of segregation by skill have implications for knowledge spillovers, innovation, wages and employment effects. According to Lucas (1988) knowledge spillovers, generated by interaction, learning by doing or imitation, are a possible explanation for persisting differences in the economic development across countries. To learn from each other face-to-face contacts and differences in the knowledge base are essential prerequisites (Jovanovic and Rob 1989; McCann and Simonen 2005). Hence, low-skilled employees might not benefit from knowledge transfer and human capital externalities released by high-skilled workers due to workplace segregation. For instance, Mas and Moretti (2009) study productivity spillovers in supermarket workgroups. They find that workers with lower productivity profit from the presence of high-productivity workers. In a laboratory experiment Falk and Ichino (2006) provide evidence for increasing productivity through peer-effects. For Italian manufacturing firms Iranzo et al. (2008) show that the productivity, and therefore the income, of the low-skilled benefit from workplaces with mixed skill composition. Braakmann (2009) uses data from German social security records and observe learning spillovers from high- to low-skilled workers at the firm level leading to higher wages for the low-skilled staff. For Portugal Martin and Jin (2010) find that education of co-workers has a significant external effect on productivity and wages within firms especially for less-educated workers. Moreover skill-specific productivity may translate into corresponding changes in employment prospects. Schlitte (2012) shows that skill segregation exerts an unfavourable effect on low-skilled employment in Western German regions. Thus, skill segregation in the production process is an important issue for regional labour market research and policy.

There are empirical studies that deal with the development of skill segregation at the national level pointing to an increasing separation of skill groups in several highly developed countries. Davis and Haltiwanger (1991) as well as Kremer and Maskin (1996) analyse the wage structure within and between firms in the U.S. manufacturing sector between 1975 and 1987. They find that the variance of wages between firms has increased more profoundly than wage disparities within firms. Based on these findings the authors conclude that the degree of skill segregation across workplaces has increased. Kramarz et al. (1996) provide evidence for increasing segregation by skill across firms in France. They show that it is more likely to find low-skilled employees at the same workplace in 1992 than in 1986. The same finding applies to high-skilled employees. Similar results for Germany are provided by Stephan (2001) analysing wage differentials within and across firms in Lower Saxony between 1994 and 2000, or by Gerlach et al. (2002) who investigate manufacturing firms between 1986 and 1992.

Overall, there is evidence for increasing levels of skill segregation in highly developed countries. However, there is a lack of studies investigating the phenomenon of skill segregation at the regional level. To the best of our knowledge this is the first analysis that considers regional disparities in segregation by skill. Furthermore, this chapter aims at identifying characteristics of regional labour markets that influence the extent of skill segregation. In particular, we focus on the effect of high-skilled labour supply on skill segregation at the workplace. Based on plant level information we use a direct measurement of skill segregation. Our findings reveal that the skill segregation is marked by pronounced regional disparities in Germany. Moreover, the results show that the local endowment with human capital is an important determinant for the regional level of skill segregation. Although local human capital is supposed to have a positive effect on regional labour markets in general, the low-skilled might benefit to a lesser extent, because they tend to work in firms with relatively less modern and less complex production technologies decreasing their productivity and employment prospects.

The rest of the chapter is organised as follows. In the next section we briefly outline theoretical explanations for increasing levels of skill segregation. Section 8.3 introduces the data set and Sect. 8.4 presents methodological issues on measuring skill segregation and the specification of our regression models. The results of our analysis are discussed in Sect. 8.5. Finally, Sect. 8.6 concludes.

8.2 Theoretical Background

There are different theoretical approaches that link rising levels of skill segregation to proceeding economic integration and to technological and organisational change (e.g. Kremer and Maskin 1996; Acemoglu 1999; Duranton 2004). Although the mechanisms differ substantially, the models have in common that the skill structure of labour supply is a key determinant for skill segregation in the production process.

According to the model by Kremer and Maskin (1996) a firm is characterised by different tasks that are complementary on the one hand but also require different skills on the other hand. Hence, different skills within a firm are not perfectly substitutable. While the complementary relation of tasks promotes joint work processes involving workers from different skill groups, the asymmetry between the tasks favours segregated work processes. Whether the tasks within a firm are accomplished by a team consisting of similar or dissimilar qualification types depends on the degree of asymmetry in qualification requirements and on the heterogeneity in the structure of skills available to firms. An increasing level of skill segregation can be released by a rising dispersion of skills within the pool of labour available to firms and by increasing differences in the skill requirements that are needed to perform the tasks.

Acemoglu (1999) proposes a search theoretic model where human capital is assumed to be complementary to physical capital. As a consequence, firms try to adapt the production technology to the skills of the work force. Because of information asymmetries the firms are not able to assess precisely the skills of potential employees beforehand. Investments in production technology, however, are made before staffing. Thus, the future internal skill structure can only be estimated by the company. This happens on the basis of the skill composition within the available pool of labour. When the supply of skills and the dispersion in the distribution of skills are relatively low, firms tend to create jobs that are suitable for a large range of skill types. While strong differences in skill levels make it easier for firms to distinguish high- from low-skilled workers, a large share of human capital raises the probability to employ a high-skilled person. Hence, in this model a rise in the supply of skills may be sufficient to release skill segregation. When the probability to hire a high-skilled person increases, more and more firms direct investments into technologies suitable to more skilled workers only. This leads to the exclusion of low-skilled workers from modern production technologies, in order to achieve higher productivity levels.

Duranton (2004) also assumes skills and technology to be complements. Each firm produces a good of a distinct quality and is either a supplier to other firms or a final good producer. Supply firms and the final good producer form a vertical production system. Because the quality of the intermediate goods has to comply with the quality of the final good, the quality level in a production system is determined by the final good producer. Furthermore, the quality of the produced good determines the complexity of the production technology and, therefore, the type of skill that is required for producing this good. Hence, aggregate production in an economy comprises vertical production systems that differ by the complexity of production process and the workers' skill level. There are two opposing forces working for or against segmentation into production systems. On the one hand, productivity gains by specialising on high-quality products are disproportionately high because of the complementary relation between physical and human capital. On the other hand, thick-market externalities that arise through a relatively large variety of intermediate goods supplied in large production systems work against segmentation. If the supply of high-skilled workers is comparatively high the relative importance of the thick-market externality declines and the incentives for firms to produce goods of a higher quality increase. Thus, with a rising share of human capital there is an increasing probability of production to be segmented into different vertical production systems that differ by the qualification levels of employees. In line with the model by Acemoglu (1999) a rising supply of high skills is sufficient to trigger skill segregation.

Closely related to the models described above, recent literature discusses more factors that may give rise to changes in the qualification structure and skill segregation. Gerlach et al. (2002) and Tsertsvadze (2005) argue that an increasing fragmentation of production processes might influence the degree of segmentation by skill. According to this reasoning, proceeding economic integration caused by a decline of transport and communication costs boosts the use of intermediate products. Hence firms outsource parts of the production process and apply specialised intermediate products (see Autor 2001). They focus thereby on the work procedures for which they possess a comparative advantage. This development results in a specialisation of the staff on certain skill types. Findings in Tsertsvadze (2005) that base on German establishment data indicate that outsourcing significantly increases the probability for a firm to develop a relatively segregated qualification structure.

In line with the models presented above, Gerlach et al. (2002) argue that characteristics of the production technology probably influence segregation at the workplace since complementarities between technology and specific qualification levels might give rise to a decline of skill diversity within firms. Since production technologies likely differ between industries and different firm sizes, region-specific sector and firm-size structures probably form a source of regional disparities in skill segregation.

Overall, the increasing level of skill segregation in highly developed countries might be explained by changes in production conditions and in the skill composition of labour supply. A rise in the dispersion of skills as well as an increasing supply of high skills may release rising levels of skill segregation.[1] Thus, the educational expansion in the 1960s and the 1970s might have generally increased the incentives for firms to apply more complex production technologies. Technological progress in turn might have raised the demand for high skills even further leading to the exclusion of less skilled workers from carrying out more complex tasks (see Griliches 1969; Lindbeck and Snower 1996). The models presented in this section provide mechanisms that link the skill structure of labour supply and changes in production conditions to skill segregation at the firm level. Hence, in our empirical analysis we focus on the role of human capital endowment as a potential determinant of regional disparities in skill segregation.

8.3 Data

We use functional regions as observational units (so-called Raumordnungsregionen) which consist of several counties (NUTS 3 regions) that are linked by intense commuting and should therefore serve as an approximation of regional labour markets. By applying functional regions most relevant processes such as job search, matching of vacancies and workers or the adjustment of firm technology to skill specific labour supply, should take place within the regions. Altogether there are 97 functional regions in Germany that we consider in the descriptive analyses. However, we have to restrict the regression analysis to the 74 West German regions since the development of skill segregation in East Germany seems to be severely affected by the transformation process of the economy in the 1990s. Moreover, East and West Germany are still marked by systematic differences in the skill structure of the work force. These disparities seem to represent, at least partly, some kind of heritage of the educational systems of the two former German states. Furthermore, the analysis takes into account the region type. Starting from a classification based on a typology of settlement structure according to the criteria population density and size of the regional centre, we differentiate between agglomerated, urbanised and rural regions.[2]

[1] Because high-skilled people are frequently associated with a relatively high mobility, the regional skill-level is crucially determined by migration. However, the consideration of interregional migration patterns is beyond the scope of this chapter.

[2] The classification has been developed by the Federal Office for Building and Regional Planning. For details see URL: http://www.bbr.bund.de/raumordnung/europa/download/spesp_indicator_description_may2000.pdf.

In the literature different measures of segregation by skill are applied. Frequently the between- and within-plant wage dispersion serves as an indicator for segregation (e.g. Davis and Haltiwanger 1991; Kremer and Maskin 1996). However, we prefer a more direct measurement of skill segregation via the formal qualification of workers. Thus, we need plant level information on employment by educational attainment. The Establishment History Panel of the Institute for Employment Research (IAB) offers corresponding annual data. The dataset contains detailed information on all establishments in Germany with at least one employee liable to social security for East and West Germany for the period 1993–2005.[3] The data include a region identifier that allows aggregation of the establishment information to the regional level. The indicators of skill segregation are based on employment data differentiated by educational attainment of the workers. We can differentiate between three levels of education: no formal vocational qualification, completed apprenticeship and university degree that are subsequently denoted un- or low-skilled, medium-skilled and high-skilled, respectively. In order to control for effects arising from the rapidly growing number of marginal part-time workers we include only full-time employees in our analysis. Furthermore, all employees that have not been assigned to an educational level were excluded from our dataset.

In the regression analysis, we include several explanatory variables that rest on information from the employment statistics of the German Federal Employment Agency for the period 1993–2005. The employment statistic covers all employment subject to social security contributions. The data is given on the NUTS 3 level and refers to workplace location. We use employment data differentiated by educational level, branch[4], occupation, and firm size in order to generate several explanatory variables.

8.4 Methodological Issues

8.4.1 Measurement of Skill Segregation

In order to investigate regional disparities in skill segregation we use a segregation measure that assesses the extent of segregation between two distinct skill groups, i.e. workplace segregation of skilled- and unskilled workers. We use the Duncan index, also called index of dissimilarity, introduced by Duncan and Duncan (1955),

[3] For a detailed description of the Establishment History Panel see: http://fdz.iab.de/en/FDZ_Establishment_Data/Establishment_History_Panel.aspx.

[4] Due to changes in the statistical recording of firms' affiliations to sectors, the information on the sector structure had to be back-dated from 1998 to earlier years. As a consequence, the data on the regional sector structure in the year prior to 1998 is only an approximation. Changes in the regional sector composition during that period might be underestimated.

which is one of the most frequently applied measures for group-specific segregation:

$$S_i = 0.5 * \sum_w \left| \frac{N_{wi}^u}{N_i^u} - \frac{N_{wi}^s}{N_i^s} \right|, \qquad 0 \le S_i \le 1 \tag{8.1}$$

where N_{wi}^u $\left(N_{wi}^s\right)$ denotes the number of unskilled (skilled) employees in workplace w and region i. The segregation measure S_i gives the proportion of low-skilled employees that has to be redistributed to other workplaces in order to get identical shares of low-skilled employees at each workplace w in region i. In case of "no segregation" the Duncan index is equal to zero. In contrast, complete segregation is indicated by a value of one.

Economic and sociological literature provides a number of alternative measures of group-specific segregation that possess different properties.[5] In contrast to the Duncan index, some of these measures are sensitive to changes in the overall group shares. This applies for example to the co-worker index introduced by Hellerstein and Neumark (2003) or the OECD measure applied by Gerlach et al. (2002). As regards to skill segregation these measures are thus affected by shifts in the regional skill shares even if the skill distribution across firms remains constant. It can be argued that changes in the relative group sizes matter for the degree of segregation irrespective of the distribution across firms. For instance, it might be reasonable to argue, that a doubling in the number of high-skilled employees in the labour force keeping constant the number of low-skilled employees increases segregation level of unskilled employees.

However, this analysis focuses on the determinants that make some firms hire predominantly skilled workers, while the others specialise on unskilled workers. According to the theoretical results discussed in Sect. 8.2 we hypothesise that the regional skill structure is a key factor regarding the incentive of firms to invest in skill-specific technologies and employ either skilled or unskilled workers. Since we include cross-sectional as well as longitudinal data in our analysis the segregation measure should be insensitive to changes in the regional skill composition. Therefore, scale invariance with respect to skill shares is a useful property for our purpose. Another useful characteristic of the Duncan index is that it is weighted by firm size. This ensures, that comparatively large firms matter more for the regional level of skill segregation than small firms.

Our segregation measure shall capture the workplace segregation of unskilled from the rest of the workforce. Hence, the group of skilled workers applied in our analysis comprises medium and high-skilled employees. In Germany, where university degree generally correspond to a master's rather than to a bachelor's level

[5] For a more extensive discussion about the properties of different segregation measures see for example Flückiger and Silber (1999) or Cutler et al. (1999).

the high-skilled represent a slightly more specific type of human capital than, for example, college degrees in the United States.[6] Hence, the relevance of joint work processes including academics and unskilled workers on the German labour market may be rather limited. Besides, the so-called dual education system, which combines formal schooling and on-the-job training produces a large number of highly skilled employees without university degree. In general, comprising a wide range of skills the group of workers with completed apprenticeship training is very heterogeneous. Overall, the cooperation between academics and unskilled workers might occur less frequent in production processes than to joint work of unskilled and medium-skilled employees, as for example an unskilled and a supervising craftsman or a technician. Therefore, the definition of skill groups in our segregation measure fits the purpose of investigating the possibility of a decoupling of unskilled workers from all other workers in the production process as pointed out by some theoretical results presented in Sect. 8.2.

8.4.2 Regression Analysis

The basic specification of the regression model that is applied to investigate the determinants of regional disparities in skill segregation links our pivotal explanatory variable, i.e. our proxy for human capital endowment, to the regional level of skill segregation:

$$S_{it} = \alpha_0 + \alpha_1 HC_{it-T} + \sum_{k=1}^{K} \beta_k C_{kit} + \tau_j + \lambda_t + u_{it} \tag{8.2}$$

where S_{it} is the level of skill segregation in region i and year t. $HC_{it-\mathrm{T}}$ is the lagged share of high-skilled workers (university degree) in total employment, τ_j is a dummy variable for the regional settlement structure j (agglomerated, urbanised, rural) and λ_t captures unobservable time effects. The error term is represented by u_{it}. Since we assume that the impact of the local skill structure on skill segregation might not be immediate, but rather works via investments in technology and sets in somewhat deferred, the share of high-skilled workers enters into the model with a time lag.

Furthermore, we expand the basic specification by some control variables C_{kit} in order to avoid misspecification due to omitted variables. Controls comprise indicators for the sectoral specialisation of regional economies and the firm size structure of employment. We include the percentages of small (up to 49 employees) and large (250 or more employees) firms in total employment and the location coefficients of 20 branches.

[6] Bachelor and master degrees have been introduced only very recently to German universities and are not an issue for the time period observed in this chapter.

There are some econometric issues in analysing the effect of high-skilled labour supply on segregation by education. The first one is the omitted variable bias that can result from the potential correlation between unobserved regional characteristics and the dependent variable, i.e. the regional level of within plant skill segregation. We can deal with time-invariant regional characteristics by applying a fixed effects model:

$$S_{it} = \alpha_0 + \alpha_1 HC_{it-T} + \sum_{k=1}^{K} \beta_k C_{kit} + \eta_i + \lambda_t + \varepsilon_{it} \tag{8.3}$$

where η_i denotes a region-specific effect, controlling for unobservable regional characteristics that are time-invariant and ε_{it} is a white noise error term. The region-specific effect will also capture any systematic differences in skill segregation between rural, urban and agglomerated regions. However, in order to estimate region-type specific effects of the local human capital endowment on the level of skill segregation, the local share of high-skilled employment enters as interaction variable with the corresponding dummy variable for the regional settlement structure τ_d (agglomerated, urbanised, rural) into the equation:

$$S_{it} = \alpha_0 + \sum_{d=1}^{3} \alpha_d HC_{it-T}\, \tau_d + \sum_{k=1}^{K} \beta_k C_{kit} + \eta_i + \lambda_t + \varepsilon_{it} \tag{8.4}$$

The second econometric issue concerns the simultaneity bias resulting from reverse causality between regional human capital and skill segregation. Due to potential endogeneity of the employment share of high-skilled labour the relationships estimated by OLS or a fixed effects model might not be interpreted as causal. According to the theoretical models outlined in Sect. 8.2, the differentiation of the regional economy into several production systems and the accompanying skill segregation likely give rise to significant differences in skill specific labour demand. Thus, we cannot assume that the regional human capital endowment is an exogenous variable. The simultaneity bias can be addressed using instrumental variable (IV) estimation. In order to identify the causal impact of high-skilled labour supply on the dependent variable, we instrument the human capital variable by time lags of the share of high-skilled workers applying two-stage-least-squares (2SLS) estimation. The lags are valid instruments if they are relevant and uncorrelated with the error term. More precisely, relevance requires a partial correlation of the instrument with the endogenous regressor, namely, the coefficient of the instrument variable should be significant in the first stage regression.

Finally, we might consider spillover effects among neighbouring labour markets. Spatial interaction should mainly take place within our observational units because we apply functional regions. However, we cannot preclude significant spillover effects across the borders of regional labour markets. Spatial dependence might be an issue although the models in Sect. 8.2 provide no theoretical arguments for important interaction among neighbouring regions as regards disparities in skill segregation. The models imply that the supply of high-skilled labour affects the firm's choice of production technology and this in turn might give rise to segregation by skill. Firms may also take into account labour supply in nearby regions when deciding on investments in technology as neighbouring labour markets are likely linked by the mobility of workers, i.e. migration and commuting. We introduce a spatial lag of human capital in the regression model to account for these effects:

$$S_{it} = \alpha_0 + \sum_{d=1}^{3} \alpha_d HC_{it-T}\,\tau_d + \rho \sum_{j=1}^{R} \omega_{ij}\, HC_{jt-T} + \sum_{k=1}^{K} \beta_k C_{kit} + \eta_i + \lambda_t + \varepsilon_{it} \quad (8.5)$$

Thus we extend the non-spatial model by a spatial lag of the pivotal explanatory variable $\sum_{j=1}^{R} \omega_{ij} HC_{jt-T}$ where ω_{ij} is an element of the $R \times R$ spatial weights matrix Ω.[7]

Taking into account the weighted sum of human capital in neighbouring regions implies that spatial autocorrelation of the error term is caused by omission of some substantive form of spatial dependence caused by neighbourhood effects. However, spatial autocorrelation in measurement errors or in variables that are otherwise not crucial to the model might also entail spatial error dependence. Provided that the unobservable common factors are uncorrelated with the explanatory variables, the coefficient estimates from the non-spatial model are still unbiased, but standard error estimates are biased and hence statistical inference that is based on such standard errors is invalid. To deal with this issue we apply the nonparametric covariance matrix estimator introduced by Driscoll and Kraay (1998), which provides heteroscedasticity consistent standard errors that are robust to very general forms of spatial and temporal dependence.[8]

8.5 Evidence on Regional Disparities in Skill Segregation Among German Regions

8.5.1 Descriptive Overview

This section illustrates the development and level of segregation by skill in the period 1993–2005. In addition to the distinction between East and West Germany we provide evidence on skill segregation for 97 functional regions and three region types that might indicate differences with respect to the regional settlement structure (agglomerated, urbanised, rural).

[7] In order to check the robustness of results with respect to variation of the spatial weighting scheme we apply two different weighting schemes. The first specification of Ω is a binary spatial weights matrix such that $\omega_{ij} = 1$ if the largest municipalities of regions i and j are within reach of not more than 100 km to each other and $\omega_{ij} = 0$ otherwise. Secondly, ω_{ij} is set to the inverse of distance between the largest municipalities of regions i and j.

[8] See Hoechle (2007) for more details.

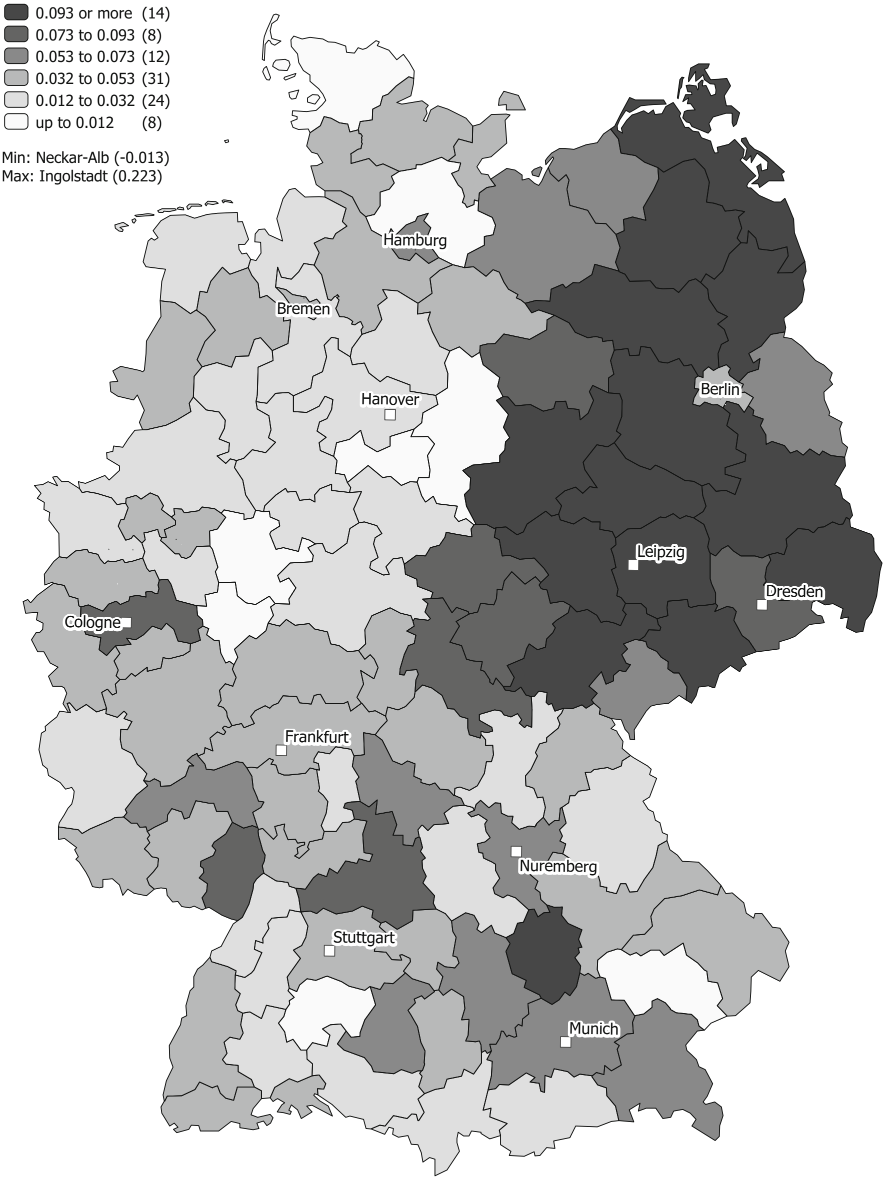

Fig. 8.1 Changes in the regional level of skill segregation 1993–2005, Duncan Index, percentage points

Skill segregation in Germany is marked by a distinctive increase in the overall level between 1993 and 2005 (see Fig. 8.1). Overall, skill segregation has been increasing in most German regions in the period under consideration. Only two out of 97 regions experienced declining levels of segregation. As shown clearly by Figure 8.1, the increase of segregation in East German regions with exception of

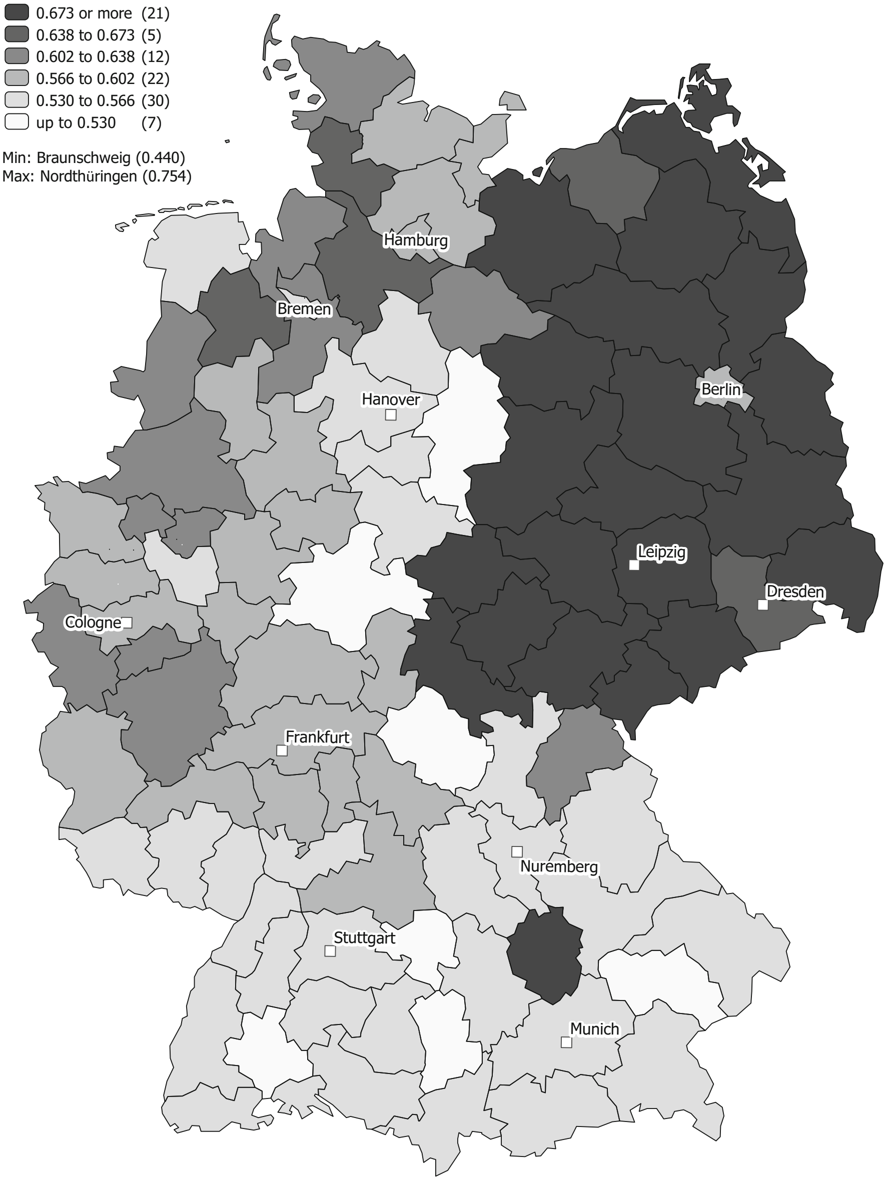

Fig. 8.2 Regional levels of skill segregation 2005, Duncan Index

Berlin is much stronger than in most West German regions. In West Germany, the heavily industrialized region of Ingolstadt in southern West Germany has experienced a particularly large increase since 1993.

Figure 8.2 indicates that there are substantial regional disparities in the levels of skill segregation across German regions in 2005. With exception of Ingolstadt, the most highly segregated regions are situated exclusively in East Germany. In the region Braunschweig, for example, 44 % of the low-skilled would have to be redistributed to other firms in order to get identical shares of low-skilled employees at each firm in 2005. By contrast in Nordthüringen 75 % of low-skilled workers would have to swap their workplace with higher skilled workers in other firms. However, segregation levels do not only differ between East and West. There is also a significant variation within East and West Germany. While the least segregated regions are mainly located in the southern part of the country, the spatial pattern in the northern part appears to be rather scattered. Along the eastern and southern boundaries of West Germany the degree of skill segregation tends to be comparatively low.

Most noticeable, the development as well as the level of skill-segregation is marked by a pronounced east–west gradient. The development of skill segregation in East German regions in the period under consideration is likely driven by the impact of economic transformation. Moreover, systematic differences in the development of the skill composition in East and West Germany in the 1990s might have affected the changes in skill segregation. For instance, findings by Fromhold-Eisebith and Schrattenecker (2006) show that the share of high-skilled employment declined dramatically while the share of low-skilled employment increased in most East German regions. This is in strong contrast to the development of the skill composition in West Germany. The profound change in the overall skill structure may have had a significant impact on the distribution of skills of across firms in East German regions. Because of the likely influence of transformation effects on the level of skill segregation in East Germany the following analyses on regional disparities in skill segregation are restricted to the West German subsample.

Figure 8.3 shows the increase in the level of skill segregation West Germany. Growth of skill segregation has been particularly pronounced during the 1990s. Since 1999, by contrast, we observe only small changes in segregation levels. Overall, this result is in line with previous findings that point to an increase of segregation by skill in developed economies. Hence, differently skilled workers tend to work more and more in different firms rather than sharing a common workplace.

Figure 8.3 further displays the development of skill segregation by different area types, i.e. agglomerated, urbanised and rural areas. Throughout the entire period agglomerated areas are characterised by a higher level of skill segregation than urbanised and rural areas. As illustrated in Figure 8.3, all area types had very similar levels of skill segregation during the 1990s. But at the end of the decade segregation in the three area types start to diverge. While skill segregation in rural areas has remained on a more or less constant level since 2000, skill segregation in urbanised and agglomerated areas has been increasing.

A possible explanation for the relatively strong ascent of segregation in agglomerated areas could lie in a more pronounced concentration of sophisticated service activities with high job requirements in agglomerations. As

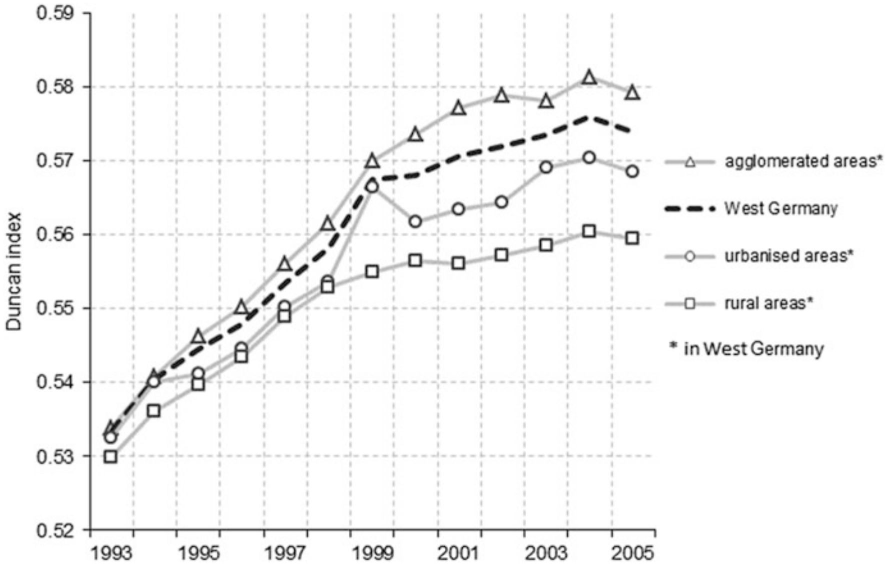

Fig. 8.3 Development of skill segregation in West Germany 1993–2005

Autor et al. (2003) show theoretically, the rise of high-skill employment is accompanied by an increasing demand for services with low-skill requirements. Hence the level of segregation rises, because high and low-skilled employees in the service sector work in separate firms.

8.5.2 Regression Results

As shown in the previous section transformation effects seem to severely influence the level of skill segregation in Eastern Germany during our period of observation. Since these effects are likely to interfere, we exclude the East German regions from the regression analysis.

Table 8.1 displays the outcome of estimating Eqs. (8.2) and (8.3) including the coefficients for the share of local high-skilled employment and region-type dummies.[9] In a first specification the human capital measure enters without time lag. However, we also consider specifications where skill shares enter with different time lags. The results of the pooled regression including dummy variables for agglomerated and rural areas show a positive impact of the local human capital share on the level of skill segregation. The significance at the

[9] The estimation results of the other control variables are not displayed, but can be obtained from the authors upon request.

10 % level is somewhat low in case of contemporaneous effects and a time lag of 1 year. However, as we increase the time lag to 2 years the coefficient slightly rises and the impact of the local human capital endowment is significant at the 5 % level for this specification. The coefficients of the dummy variables point to systematic differences between region types. In particular, the level of skill segregation in rural areas differs from those in the reference category, i.e. the urbanised areas.

The fixed effects estimations account for these differences as well as for other unobserved time-constant characteristics. The results indicate that the impact of high-skilled labour supply is not immediate. The unlagged share of high-skilled workers yields a positive but insignificant coefficient. However, the corresponding coefficients are largest in size and statistically significant with a lag of two periods (at the 1 % level). Hence, the findings suggest that the regional level of skill segregation is positively affected by previous shares of local human capital. This might reflect that investments in skill-specific technologies and its impact on skill segregation due to changes in the supply of human capital take some time. According to these results growth of the workforce with tertiary education gives rise to an increasing segregation between the low-skilled and the rest of all employees within a time span of about 2 years time.

Table 8.2 provides results for the estimation of Eqs. (8.4) and (8.5), i.e. with and without considering a spatial lag of human capital in the regression model, both including our proxy for local human capital as well as employment shares of small and large firms and location coefficients of various branches. We focus on the specification with human capital indicator lagged by 2 years. In order to account for differences in the impact of human capital on skill segregation among region types we include interaction terms of the local share of high-skilled employment and the region type dummies. In addition to standard fixed effects estimations, the table presents the estimates obtained by applying Driscoll and Kraay standard errors and IV estimation. The findings of the standard fixed effects model (Eq. 8.4) confirm our previous results suggesting that the regional level of skill segregation is significantly and positively affected by local human capital (significant at the 1 % level for all region types). [10]

The results of the 2SLS estimations suggest that endogeneity of the regional human capital endowment is unlikely to be a major problem. We apply the share of high-skilled workers lagged by 6 years as an instrument for human capital. According to the first-stage regressions the interaction variables of the share of high-skilled lagged by six periods and the corresponding region type dummies are valid instruments. The high significance (at the 1 % level) of the instruments in the first stage regression indicates that the partial correlation between the

[10] In contrast our previous results the fixed effects estimates indicate that there is an immediate impact of high skilled labour supply in urbanised areas. However, the size of the estimated impact increases with a lag of two periods. Overall, this confirms that changes in the supply of human capital take some time to exert influence on the level of local skill segregation. Corresponding estimation results are available from the authors upon request.

instruments and the endogenous explanatory variables is sufficient to ensure unbiased estimates and relatively small standard errors.[11] The impact of regional human capital endowment on skill segregation is even reinforced in the IV regressions. For all three region types the corresponding coefficients are highly significant and larger in size compared to the standard fixed effects estimations. According to IV estimation results an increase in the share of high-skilled employment by 1 percentage point increases the level of segregation, i.e. the share of unskilled employees that has to be redistributed in order to maintain no skill segregation, by 0.71 percentage points in agglomerations, 1.51 percentage points in urbanised areas and 1.63 percentage points in rural areas. Thus regional segregation levels are positively affected by increasing local human capital endowment irrespective of the settlement structure. However, the impact seems to be smaller in agglomerated areas as compared to urbanized and rural regions. Hence, the consequences of an increase of the relatively high initial shares of human capital in agglomerations is comparatively small.

The IV estimates are positive, significant, and larger than their simple fixed effects counterparts. This is surprising since simultaneity should result in upward biased fixed-effects estimates of the impact of human capital. This suggests that the simultaneity bias in the fixed effects estimates is relatively small. The gap between fixed effects and IV estimates might reflect a downward bias in the fixed effects estimates caused by measurement errors. This may indicate that the measurement error's bias towards zero is more important than the upward bias due to the impact of segregation on the regional human capital. Another explanation is that there is heterogeneity in the effect of high-skilled labour supply on skill segregation, and that the IV estimates tend to recover effects for a subset of regions with relatively strong impact of human capital on segregation.[12]

Including the spatially lagged share of high-skilled employment (Eq. 8.5) does not ultimately change these findings. For instance, applying a binary spatial weights matrix as specified above does only slightly affect the size as well as the significance of the estimates for local skill supply in Table 8.2. The corresponding coefficients of the interaction variables in the spatial models are somewhat below those in the non-spatial model. The marginal effects in the spatial IV model for example decline from 0.71 to 0.64 for agglomerated areas, from 1.51 to 1.40 for urbanised areas and from 1.63 to 1.50 for rural regions. Thus, ignoring spatial dependence yields a small upwards bias in the estimates for the local skill supply but does not alter our main conclusions. The coefficients of the spatially lagged variable are significant and positive for each model specification. However, while the estimates for local skill supply are

[11] The first-stage estimation results can be obtained from the authors upon request.

[12] See Card (2001) for a corresponding reasoning with respect to returns to schooling.

robust to changes in the specification of the spatial weight matrix the coefficients of the spatially lagged skill shares are sensitive to alternative weighting schemes.[13] Increasing the distance cut-off, that is expanding the area of surrounding regions considered for spatial interaction, to 150 and more kilometres decreases the coefficients' size and ultimately results in effects that do not significantly differ from zero. Overall, this indicates that firms take into account labour supply in nearby regions, i.e. within reach of 100 km, when deciding on investments in technology.

Furthermore, the results of the standard fixed effects estimation do not alter by applying Driscoll and Kraay (1998) standard errors that are robust to heteroscedasticity and general forms of cross-sectional and time series autocorrelation. Columns 3 and 4 in Table 8.2 show the fixed-effects estimates (Eq. 8.4) with robust standard errors. Thus, we can preclude spatial autocorrelation in measurement errors, such as a wrongly defined regional system to seriously affect statistical inference.

The coefficients of the control variables show that both the firm-size structure and specialisation of the regional economy on specific branches matter for the level of segregation by skill. The coefficient of the employment share of small firms is significantly negative. Thus, the phenomenon of segregation between skilled and unskilled workers seems to be less pronounced in regional labour markets characterised by large share of small firms. The results for the location coefficients of specific branches show that for the majority of the manufacturing branches specialisation of the regional labour market tends to correlate negatively with segregation by skill. However, large shares of the branches "Food, Drink and Tobacco", "Textiles and Leather" and "Motor Vehicles" show significantly positive coefficients. Regarding the rest of the manufacturing most of the estimated effects are significantly negative. By contrast, in the service sector the majority of the coefficients show positive signs. However, the branches "Finance and Insurance" and "Temporary Employment" also exert a negative influence on skill segregation. Altogether, these findings suggest that sectoral specialisation has differentiated influence on skill segregation. Whereas some branches tend to boost segregation by skill, other industries seem to dampen the regional intensity of segregation.

Overall our empirical models explain a significant part of the regional disparities in skill segregation. According to the R^2 of the within estimators around 63 % of the (within) variation can be explained by our model. Moreover, the results show that the local supply of skilled labour is indeed a key determinant as regards the regional development of within-firm segregation by skill, which is in line with the theoretical models discussed in Sect. 8.2.

[13] The results applying alternative weighting schemes can be obtained upon request from the authors.

8.6 Conclusions

Our analysis aims at investigating regional disparities in workplace segregation by skill and its determinants. While previous analyses examine skill segregation mainly on the national level, we provide first evidence on regional disparities in segregation by skills. Applying the Duncan index on regional and firm-level data we investigate skill segregation at the regional level, namely segregation between unskilled and the rest of all workers. The results point to pronounced regional disparities in the level of skill segregation across German regions. Furthermore, the development of skill segregation is marked by a distinctive increase between 1993 and 2005. Due to transformation process in the 1990s and systematic differences in the qualification structure between East and West Germany the development and levels of skill segregation differ substantially between both parts of the country. In contrast, we detect only small disparities between urban and rural areas by the end of the 1990s. However, since 2000 the development of segregation across different region types seems to diverge. Especially, in more densely populated areas the relatively strong increases in the level of skill segregation may negatively impact the employment prospects for the low-skilled.

The regression analysis reveals significant effects of the local skill composition on the level of skill segregation. Skill segregation is positively affected by a large local supply of human capital. We assume that the effect of the local skill structure works via investments in technology and sets in somewhat deferred. Applying different time lags demonstrates that the impact of the local skill supply on segregation levels is not immediate, but sets in with a delay of about 2 years. The marginal effect of a change in the local level of human capital is smaller in agglomerated regions than in urbanised and rural areas. Thus, the impact of a further increase of the already relatively high levels of human capital in large urban regions on skill segregation is comparatively small. Furthermore, including a spatially lagged share of human capital in our regression model shows that firms also take the skill supply in nearby regions into account when making decisions on investments in production technology. This, however, does not significantly affect the estimates of our proxy for the local supply of human capital.

Overall, our findings are in line with theoretical results providing a link between proceeding division of labour and technological change on the one hand and rising levels of skill segregation in the production process on the other hand. In the corresponding models the supply of human capital is a key determinant for the segmentation of skills in the production process. For Germany as a highly developed country we identify an important factor with respect to increasing skill segregation. Furthermore, our findings indicate that sectoral specialisation as well as the firm-size structure matter for the regional level of skill segregation. This possibly reflects different skill compositions across firm-size classes and branches. The latter can be explained by differences in production technologies.

The theoretical results discussed in Sect. 8.2 further propose a link between skill segregation and rising wage inequalities as well as the possibility of adverse effects on low-skilled employment. Schlitte (2012) provides evidence on adverse effects of segregation on labour market prospects of low-skilled. Thus, due to adverse effects from skill segregation the low-skilled might benefit less from the positive labour market effects of local human capital that are frequently found in the literature. Considering a negative impact of skill segregation on the productivity and employment prospects of low-skilled workers our findings have important implications for regional labour market policy. Local policy makers might take skill segregation into account when tackling the problem of high unemployment rates or unfavourable working conditions at the lower bound of the skill distribution. However, in order to specific policy measures additional research on the mechanisms behind the effects of local human capital, skill segregation and their interplay might be necessary.

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Appendix

Table 8.1 Estimation results (Eqs. 8.2 and 8.3)

Model	Pooled regression (Eq. 8.2)			Fixed effects (Eq. 8.3)		
Time lag on skill share	No	1 year	2 years	No	1 year	2 years
Skill share	0.130* (0.069)	0.136* (0.071)	0.150** (0.073)	0.168 (0.113)	0.231** (0.111)	0.335*** (0.111)
Dummy agglomerated area	0.004 (0.003)	0.004 (0.003)	0.004 (0.003)	–	–	–
Dummy rural area	−0.019*** (0.003)	−0.019*** (0.003)	−0.019*** (0.003)	–	–	–
R^2_within	0.759	0.759	0.759	0.627	0.628	0.630
No. of obs.	962	962	962	962	962	962

Notes: *** significant at the 0.01-level; ** significant at the 0.05-level, * significant at the 0.1-level. Standard errors reported in parentheses

Table 8.2 Estimation results (Eqs. 8.4 and 8.5)

Model	FE		FE-Robust		IV	
Skill share * metropolitan area (lagged by 2 years)	0.311**	0.284**	0.311**	0.284**	0.710***	0.635***
	(0.111)	(0.110)	(0.137)	(0.118)	(0.135)	(0.133)
Skill share * urban area (lagged by 2 years)	0.765***	0.728***	0.765***	0.728***	1.508***	1.396***
	(0.153)	(0.152)	(0.129)	(0.108)	(0.196)	(0.193)
Skill share * rural area (lagged by 2 years)	0.634***	0.581**	0.634**	0.581**	1.627***	1.496***
	(0.233)	(0.231)	(0.215)	(0.202)	(0.290)	(0.286)
Spatially lagged skill supply (lagged by 2 years)	-	0.976***	-	0.976***	-	1.077***
		(0.239)		(0.138)		(0.277)
Small firms	−0.235***	−0.219***	−0.235**	−0.219**	−0.206***	−0.192***
	(0.072)	(0.072)	(0.082)	(0.080)	(0.073)	(0.073)
Large firms	−0.006	0.000	−0.006	0.000	−0.017	−0.010
	(0.050)	(0.050)	(0.071)	(0.068)	(0.051)	(0.050)
Food, Drink & Tobacco	0.021***	0.020***	0.021***	0.020***	0.019***	0.018***
	(0.006)	(0.006)	(0.004)	(0.005)	(0.006)	(0.006)
Textile & Leather	0.008***	0.009***	0.008**	0.009**	0.008***	0.009***
	(0.003)	(0.002)	(0.004)	(0.004)	(0.003)	(0.003)
Wood	0.000	−0.002	0.000	−0.002	0.001	−0.001
	(0.003)	(0.003)	(0.001)	(0.001)	(0.003)	(0.003)
Paper & Printing	−0.028***	−0.025***	−0.028***	−0.025***	−0.030***	−0.028***
	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.007)
Chemistry and Synthetic Materials	−0.014***	−0.012***	−0.014**	−0.012**	−0.015***	−0.013***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Glass & Ceramics	−0.005*	−0.004	−0.005**	−0.004**	−0.007**	−0.006**
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
Metal-Production & Manufactoring	−0.018***	−0.016***	−0.018**	−0.016**	−0.016***	−0.014**
	(0.005)	(0.005)	(0.007)	(0.006)	(0.005)	(0.005)
Machinery	0.001	0.001	0.001	0.001	0.001	0.000
	(0.004)	(0.004)	(0.003)	(0.003)	(0.005)	(0.004)

(continued)

Table 8.2 (continued)

Model	FE		FE-Robust		IV	
Electrical Engineering	−0.018***	−0.016***	−0.018***	−0.016***	−0.019***	−0.017***
	(0.005)	(0.005)	(0.003)	(0.002)	(0.005)	(0.005)
Motor Vehicles	0.005*	0.005*	0.005	0.005	0.007**	0.006**
	(0.003)	(0.003)	(0.006)	(0.006)	(0.003)	(0.003)
Building & Construction	0.007	0.006	0.007	0.006	0.018*	0.016
	(0.009)	(0.009)	(0.007)	(0.006)	(0.010)	(0.009)
Commerce	−0.019	−0.027	−0.019*	−0.027**	−0.017	−0.027
	(0.017)	(0.017)	(0.010)	(0.010)	(0.017)	(0.017)
Hotels & Gastronomy	0.022***	0.024***	0.022***	0.024***	0.026***	0.028***
	(0.008)	(0.007)	(0.005)	(0.005)	(0.008)	(0.008)
Information & Transportation	0.012*	0.008	0.012**	0.008	0.014**	0.010
	(0.007)	(0.007)	(0.005)	(0.005)	(0.007)	(0.007)
Finance & Insurance	−0.038***	−0.033***	−0.038*	−0.033	−0.042***	−0.036***
	(0.012)	(0.012)	(0.020)	(0.019)	(0.012)	(0.012)
Simple Business-Related Services	−0.013**	−0.016**	−0.013**	−0.016***	−0.009	−0.012**
	(0.006)	(0.006)	(0.004)	(0.004)	(0.006)	(0.006)
Complex Business-Related Services	0.027***	0.024***	0.027*	0.024	0.023***	0.020***
	(0.007)	(0.007)	(0.014)	(0.013)	(0.007)	(0.007)
Temporary Employment	−0.004*	−0.005**	−0.004*	−0.005**	−0.005*	−0.006**
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
Education	0.007*	0.008*	0.007	0.008*	0.010**	0.010**
	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)
Health & Social Services	0.009	0.006	0.009	0.006	0.006	0.003
	(0.012)	(0.012)	(0.011)	(0.010)	(0.012)	(0.012)
Constant	0.666***	0.583***	0.666***	0.589***	0.583***	0.507***
	(0.054)	(0.057)	(0.036)	(0.056)	(0.042)	(0.061)
$\mathbf{R^2}$	0.638	0.645	0.638	0.645	0.628	0.637
No. of obs.	962	962	962	962	962	962

Notes: *** significant at the 0.01-level; ** significant at the 0.05-level, * significant at the 0.1-level. Standard errors reported in parentheses

References

Acemoglu D (1998) Why do new technologies complement skills? Directed technical change and wage inequality. Q J Econ 113(4):1055–1089

Acemoglu D (1999) Changes in unemployment and wage inequality: an alternative theory and some evidence. Am Econ Rev 89(5):1259–1278

Acemoglu D (2002) Directed technical change. Rev Econ Stud 69(4):781–809

Autor DH (2001) Wiring the labor market. J Econ Perspect 15:25–40

Autor DH, Levy F, Murnane RJ (2003) The skill content of recent technological change: an empirical exploration. Q J Econ 118(4):1279–1333

Braakmann N (2009) The role of firm-level and regional human capital for the social returns to education – evidence from German social security data. Working paper series in Economics (126)

Card D (2001) Estimating the returns to schooling: progress on some persistent econometric problems. Econometrica 69:1127–1160

Cutler DM, Glaeser EL, Vigdor JL (1999) The rise and decline of the American Ghetto. J Polit Econ 107(3):455–506

Davis S Haltiwanger J (1991) Wage dispersion between and within U.S. manufacturing plants, 1963–86. Brooking papers on economic activity, Microeconomics, pp 115–180

Driscoll J, Kraay AC (1998) Consistent covariance matrix estimation with spatially dependent data. Rev Econ Stat 80:549–560

Duncan OB, Duncan B (1955) A methodological analysis of segregation indexes. Am Sociol Rev 20:210–217

Duranton G (2004) The economics of production systems: segmentation and skill-biased change. Eur Econ Rev 48:307–336

Falk A, Ichino A (2006) Clean evidence on peer effects. J labor econ 24(1):39–58

Flückiger Y, Silber J (1999) The measurement of segregation in the labor force. Physica, Heidelberg

Fromhold-Eisebith M, Schrattenecker W (2006) Qualifikationsentwicklung der Beschäftigten in Deutschland. Eine raumbezogene Analyse. Raumforschung und Raumordnung 64(4):258–269

Gerlach K, Meyer W, Tsertsvadze G (2002) Entwicklung der qualifikatorischen Segregation im Verarbeitenden Gewerbe. Betrieblicher Wandel und Fachkräftebedarf -, Beiträge zur Arbeitsmarkt- und Berufsforschung 257:51–80

Goos M, Manning A (2007) Lousy and lovely jobs: the rising polarisation of work in Britain. Rev Econ Stat 89(1):118–133

Griliches Z (1969) Capital-skill complementarity. Rev Econ Stat 51(4):465–468

Hellerstein J, Neumark D (2003) Workplace segregation in the united states: race, ethnicity and skill. Rev Econ Stat 90(3):459–477

Hoechle D (2007) Robust standard errors for panel regressions with cross-sectional dependence. Stata J 7(3):281–312

Iranzo S, Schivardi F, Tosetti E (2008) Skill dispersion and firm productivity: an analysis with employer-employee matched data. J Labor Econ 26(2):247–285

Jovanovic B, Rob R (1989) The growth and diffusion of knowledge. Rev Econ Stud 56 (4):569–582

Karmarz F, Lollivier S, Pelé L-P (1996) Wage inequalities and firm-specific compensation policies in France. Annales d'Economie et de Statistique 41/42:369–386

Kremer M, Maskin E (1996) Wage inequality and segregation by skill, NBER Working Paper 5718

Lindbeck A, Snower DJ (1996) Reorganization of firms and labor-market inequality. Am Econ Rev 86(2):315–321

Lucas RE (1988) On the mechanics of economic development. J Monet Econ 22(1):3–42

Manning A (2004) We can work it out: the impact of technological change on the demand for low-skilled workers. Scot J Polit Econ 51(5):581–608

Martins PS, Jin JY (2010) Firm-level social returns to education. J Popul Econ 23(2):539–558
Mas A, Moretti E (2009) Peers at work. Am Econ Rev 99(1):112–145
McCann P, Simonen J (2005) Innovation, knowledge spillovers and local labour markets. Pap Reg Sci 84(3):465–485
Nickel SJ, Bell BD (1995) The collapse in demand for the unskilled and unemployment across the OECD. Oxford Rev Econ Pol 11(1):40–62
Schlitte F (2012) Local human capital, segregation by skill, and skill-specific employment growth. Pap Reg Sci 91(1):85–107
Spitz-Oener A (2006) Technical change, job tasks, and rising educational demands: looking outside the wage structure. J Labor Econ 24(2):235–270
Stephan G (2001) Firmenlohndifferenziale. Eine Analyse für die Bundesrepublik Deutschland. Campus, Frankfurt/New York
Tsertsvadze G (2005) Qualifikatorische Segregation: Entwicklung und Bestimmungsgründe; eine theoretische und empirische Analyse. Shaker, Aachen
Wood A (1994) North–south trade, employment and inequality. Changing fortunes in a skill-driven world, IDS development studies series. Clarendon Press, Oxford
Wood A (2002) Globalization and wage inequalities: a synthesis of three theories. Weltwirtschaftliches Archiv 138(1):54–82

Chapter 9
Interregional Migration 'Wage Premia': The Case of Creative and Science and Technology Graduates in the UK

Sarah Jewell and Alessandra Faggian

9.1 Introduction

Since the seminal contribution by Sjaastad (1962), the so-called 'human capital migration theory' has become extremely popular among economists, especially regional economists. The basic idea is that migration itself can be viewed as an investment in human capital. A rational individual would use relocation as a means to maximize long-term utility and would move if the future discounted benefits of relocating outweigh the costs associated with the move.

For working-age individuals, one key element of the 'future benefit' is labor income, so finding a good job is a crucial element in the decision to migrate. Kennan and Walker (2011) show how in the USA interstate migration decisions are influenced to a substantial extent by income prospects. This is particularly true if the individuals are also relatively young and well-educated, as migration is a potential way to increase returns to education (Becker 1993). Not surprisingly, many empirical contributions find a positive relationship between the level of education and the likelihood to migrate. The better educated are indeed reaping the highest returns from the migration process (Sabot 1987). This is not only because migration increases their chances of finding the best job match for their abilities, hence increasing the stream of future benefits, but also because the migration process for the young and educated has lower costs. Highly educated individuals are better in finding and processing information, less reliant on family and friends and, in general, more adaptable to new living conditions.

S. Jewell (✉)
Department of Economics, University of Reading, Whiteknights, Reading RG6 6AA, UK
e-mail: s.l.jewell@reading.ac.uk

A. Faggian
AED Economics Department, The Ohio State University, 2120 Fyffe Road Columbus, OH 43210, USA
e-mail: faggian.1@osu.edu

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The aim of this chapter is to analyze the migration behavior of graduates from UK universities with a focus on the salary benefits they receive from the migration process. While a wide array of studies exists on the determinants of migration (both international and interregional) and on the salary effects of international migration (both on the resident population and immigrants), surprisingly few contributions focus specifically on the effects of interregional migration on salaries or individual income. However, the large majority of students and graduates in the UK move out of their original place of residence to study and work elsewhere each year (Faggian et al. 2006, 2007a; Faggian and McCann 2009a, b), which implies that migration has to have clear benefits. Our model provides an initial estimate of these benefits. It differs from previous studies in that it accounts explicitly for migrant selectivity and it also classifies graduates into different migration behavior categories (following Faggian 2005) to assess the effect of each migration behavior on salaries. Moreover, given the recent debate on the role of creative individuals and creative industries in the UK, we also pay particular attention on the heterogeneity of graduates with regards to the subject studied and compare 'creative' graduates (which we will call 'Bohemian graduates' following Comunian et al. 2010; Faggian et al. 2013 and Abreu et al. 2012) with graduates from more hard-core science graduates (also known as STEM, i.e. science, technology, engineering and mathematics graduates), which have also received a lot of recent attention especially from policy makers (BICS 2011; UKCES 2011).

This chapter is organized as follows. Section 9.2 provides a basic framework for our work and a brief overview of the few contributions on the topic. Section 9.3 describes the data we are using and the methodology we adopt. Section 9.4 presents the results and discusses them. Finally, the last section provides some preliminary conclusions, policy implications and avenues for future work.

9.2 Interregional Migration and Salaries

While many studies address the effect of international migration on the salaries of the native-born population (Borjas 1995; Card 2001; Greenwood et al. 1996; Ottaviano and Peri 2005; Shierholtz 2010) and a substantial body of literature focuses on the determinants of interregional migration in different countries,[1] not many studies have examined the relationship between salaries and interregional migration. Moreover, among the contributions, which explicitly model the relationship between interregional migration and salaries, only a handful recognizes and tackles the problem of migrant selectivity.

The contribution by Lansing and Morgan (1967) is probably one of the first to explicitly analyze the effect of intra-national mobility on individual income.

[1] See Greenwood (1975) for a review focused on the US case and Jayet (1996) for a review of studies outside the US.

By looking at the case of the US in the 1960s, they conclude that income levels of geographically mobile workers are less than those of non-mobile workers. This result, which is counter to the human capital migration theory, is explained by the fact that mobile workers are also more likely to change occupation and/or industry together with location and this might come with an initial penalty. However, as Gallaway (1969) points out in a subsequent comment, their results also show the need to compare ‘like with like’. When the comparison is restricted to groups of workers with similar characteristics, the negative relationship between interregional mobility and income tends to disappear.

Most of the studies published in the 1970s also did not account for the migrant selectivity problem (e.g. Mincer and Jovanovic 1979), hence producing estimates where the effect of migration itself was inter-mixed with the effect of the different personal characteristics of migrants vs. non-migrants. The first to propose a method to solve the migration selectivity problem were Nakosteen and Zimmer (1982). They proposed the use of a Heckman two-stage procedure to correct for self-selectivity. The first step is a probit model of the likelihood to be a migrant, while the second stage is an OLS estimation of an earning equation for migrants *à la* Mincer where an extra ‘selectivity bias term’ (termed the inverse mills ratio) – derived from the probit model – is included. Essentially, the new ‘selectivity bias term’ corrects for the fact that the earning equation in the second stage is estimated only on a subsample of observations not randomly selected from the total population. While this is a viable procedure, one problem is that the error term associated with the earning equation in the second stage is not homoscedastic.

Despite this problem, the Nakosteen and Zimmer (1982) approach became quite popular and it is still widely used. Détang-Dessendre et al. (2004) for instance use the Nakosteen and Zimmer’s (1982) approach to study the impact of migration on the wages of young French people entering the labor market. They find a positive self-selection for highly educated migrants, while there is no selection bias for workers with low levels of education, suggesting that differences in productivity among low skilled migrants and not migrants are negligible. Nakosteen and Westerlund (2004) studying the case of Sweden find a positive relationship between interregional migration and gross labour income. Although they do not use a propensity score matching techniques, they do control for selectivity by means of a treatment-effect model *à la* Greene (2000).

Another way of tackling the problem of selectivity of migrant has been to just present separate estimates for different sub-group of the population, since different sub groups may have different propensities to migrate. Yankow (2003), for instance, studying the case of the USA, finds an overall salary associated with migration of about 10 %, but also gives separate estimates for different sub-group of migrants, e.g. highly vs. low educated (11.3 % vs. 8.1 %), white men vs. black or Hispanic men (10.2 % vs. 8.1 % and 6.9 % respectively). A similar approach is also used by Lehmer and Möller (2008) in the case of Germany. They find an overall effect of interregional migration on earnings of about 2.5 % and they also produce estimates for sub-groups of the population based on skill levels (high, medium, low), firm size (small, medium, large) and region of employment (four macro-region in Germany).

Although their main models are estimated by simple OLS, they do present a robustness check where they try out a simple propensity score matching approach for the whole sample and they conclude that the two methods give similar results.

While the previous contributions present interesting results, they do not completely correct for the problem of migrant self-selectivity. Our approach is to use a propensity score matching methodology (PSM). PSM is used extensively in policy evaluation and it is superior to standard OLS models because it is a non-parametric technique, which does not assume linearity between the dependent and independent variables hence avoiding misspecification issues. The only example of contribution using explicitly a propensity score matching method to evaluate the effect of interregional migration on migrant salaries is the paper by Di Cintio and Grassi (2013). Studying the case of Italian graduates, and using a Kernel propensity score matching method, they find that 'late movers' (i.e. individuals who studied locally, but moved after graduation) had a salary premium from migration of about 15.3 %. However, due to data limitation, their definition of '*migrant*' is rather coarse, as they can only split Italy into four macro-areas (North West; North East; Centre and South) and define a migrant as somebody who moves across these macro areas. Moreover, most of the salary advantage might be the result of just a one-directional migration flow from the South to the North. A different definition of 'migrant' (e.g. across regions) might give different results. Moreover, in their contribution there is no sensitivity analysis for the goodness of the matching (e.g. by trying different matching procedures or by providing a measure for the quality of their Kernel matching).

Although our approach is similar to Di Cintio and Grassi (2013), our data allows for a much more refined definition of migrant. Not only can we use smaller areas, but we can also clearly identify the length moved by each individual as we know the postcode of their initial origin and final destination. This also means that we do not have to rely on administrative units to discriminate between migrants and non-migrants but rather we used a threshold on the actual distance moved.

9.3 Data and Definitions

Our main data source is the Destinations of Leavers in Higher Education (DLHE) survey, undertaken annually on behalf of the Higher Education Statistics Agency (HESA) by all UK Higher Education Institutions (from now on referred to as HEIs) to collect data on the job conditions of British graduates 6 months after graduation. In particular the DLHE data contains information on student job location, salary, occupation and industry of employment. We matched the DLHE to the student records also collected by HESA, which contains information on students' personal characteristics (age, ethnicity, gender), course details (subject studied, mode of study, i.e. part-time vs. full-time), institution attended, qualifications on entry, degree classification and postcode of domicile before entering university.

In this chapter we look in particular at the 2004/2005 graduate cohort and focus on full time[2] British domiciled students who graduate with a first degree. This is because the DLHE survey is targeted particularly at British domiciled students and hence response rates from this group are quite high (around 75 %) compared to overseas (EU) students (a target rate of 50 %). Moreover, to classify graduates according to their migration behaviour we need to calculate the distances moved by students from their original domicile (before entering university) to university and later on from university to first job location. This is possible only for observations for which we have the full postcodes of their original domicile, university attended and their first job. Therefore overseas students also do not have a postcode attached to their original domicile (as it was abroad by definition) so cannot be classified according to their sequential migration behaviour. Open University students were also dropped since they are enrolled in distance learning courses, which often do not require the student to physically move to the university location.

Our sample consists of 176,217 of which 72 % (126,061) entered the labour market in some capacity: 54 % full-time, 8 % part-time, 1 % in voluntary and unpaid work and 8 % working and studying. After removing the observations for which we did not have information on either location or salary we were left with 54,186 valid observations. There was no systematic bias in this sub-sample compared to the initial sample. There is also a potential bias for wage rates from graduates not entering the labour market e.g. because they go on to further study or are unemployed, but past work indicates this bias is not significant (Ireland et al. 2009; Jewell 2008; Naylor et al. 2007) and we interpret our results as conditional on entering employment.

Following Faggian (2005), students were classified according to their 'sequential migration behaviour', i.e. whether they migrate to go to university and whether they – later on – migrated from university to employment. Migration is defined as a movement greater than 15 km (even though 50 km was also used for robustness check). The combination of these two migration decisions has five possible outcomes, depicted in Fig. 9.1.

Students were also classified according to the subject studied. In particular, we were interested in differentiating 'creative' graduates from more 'hard-science' graduates (also known as STEM, i.e. science, technology, engineering and mathematics, graduates). The definition of creative subjects was based on the definition used by Faggian et al. (2013) and typically covers creative art and design, media and architecture graduates. STEM subjects were defined using a definition similar to that of several government reports (BICS 2011; Oxford Economics 2009; UKCES 2011). All subjects not covered by the STEM or creative subject definitions

[2] We excluded students who studied part time because they are generally much older and less likely to migrate because of family ties, or because their degree is an integrated part of their employment. Secondly the response rates of part time students (around 60 %) are lower than those of full time students.

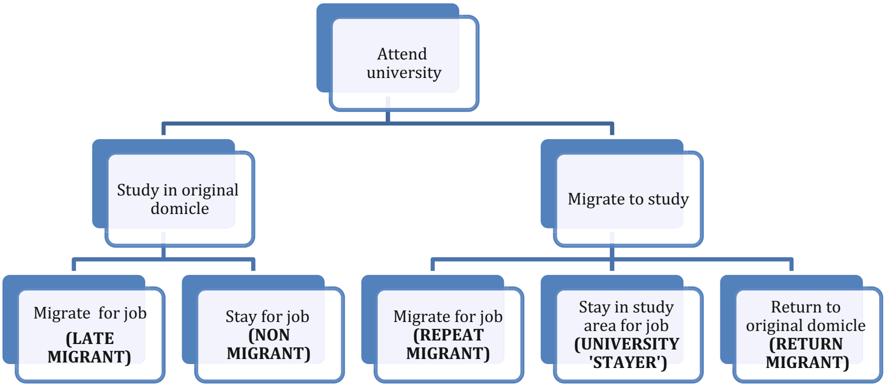

Fig. 9.1 Sequential migration categories

Table 9.1 Sample composition by subject studied

	Freq.	Percent
STEM	64,846	36.8
Creative	27,909	15.84
Other	83,462	47.36
Total	*176,217*	*100*

were grouped under 'other' subjects.[3] See the Appendix for full details of the subject definition.

Based on the above definition, 37 % of students graduated in a STEM subject, 16 % in a creative subject and 47 % in 'other' subjects (Table 9.1).

Although subject did not have a significant impact on the percentage of graduates finding full-time paid employment shortly after graduating, in particular creative graduates were more likely to be in part-time employment and less likely to be in 'further studies' than the rest of the sample (Table 9.2).

The main difference between 'creative' and STEM graduates is the average salary when entering the labour market. STEM graduates command a salary which is over £2,500 higher than creative graduates (Table 9.3). This is not surprising and it is consistent with previous findings. Comunian et al. (2010) discusses at length the possible reasons for the poor labour economic conditions of creative (or 'Bohemian') graduates and it is beyond the scope of this chapter to discuss them here.

Migration patterns also vary by subject group with STEM and creative graduates both more likely to migrate in some form than other graduates. STEM students are the most likely to be repeat or late migrants with creative graduates more likely to be university stayers or return migrants. What it is noteworthy for the scope of this chapter is that migration seems to have a much higher associated 'premium' for STEM graduates, than for creative graduates. If we compare the average salary

[3] Note that medicine and dentistry students were omitted, given they are salary outliers and the majority do not have a degree classification.

Table 9.2 Working conditions after 6 months by subject group

	STEM	Creative	Other	Total
Full-time paid work	54.63	54.95	53.51	54.15
Part-time paid work	7.2	11.64	7.75	8.16
Voluntary/unpaid work	0.83	1.18	0.96	0.95
Work and study	7.94	7.5	8.79	8.27
Further study only	16.27	9.69	16.67	15.42
Assumed to be unemployed	7.16	8.85	5.79	6.78
Not available for employment	4.85	4.6	5.5	5.12
Other	1.12	1.59	1.01	1.14
Total	*100*	*100*	*100*	*100*

Table 9.3 Average salaries by subject group and migration category

	%	Average salary
STEM		
Non-migrant	15.3	16,783
Late migrant	6.1	18,157
University stayer	17.3	16,983
Return migrant	27.8	15,879
Repeat migrant	33.6	18,854
Total	***100***	***17,452***
CREATIVE		
Non-migrant	14.8	15,092
Late migrant	4.3	15,539
University stayer	20.7	14,516
Return Migrant	31.2	13,918
Repeat Migrant	29.1	15,693
Total	***100***	***14,861***

of the most 'migratory' group of graduates, i.e. repeat migrants, with the least migratory group, i.e. non-migrants, migration premium seems to be about £2,000 for STEM graduates while it is only £600 for creative graduates. It would be, however, incorrect to draw conclusions on the 'migration premia' from just some simple descriptive statistics, without controlling for other factors and, most importantly without correcting for possible migrant self-selectivity. Our modelling strategy to tackle these issue is described in the next session.

9.4 Modelling Strategy

Our modelling strategy is a two-step strategy. First, we estimate a simple earning equation *à la* Mincer using OLS (corrected for heteroskedasticity) where we include among the explanatory variables also dummies for the different sequential migration behaviour categories (using non-migrant as the base category):

$$\log w^j = \alpha^j + \beta \boldsymbol{IND^j} + \gamma \boldsymbol{HEI^j} + \delta_1 REPEAT + \\ + \delta_2 RETURN + \delta_3 UNISTAY + \delta_4 LATE + \varepsilon^j \tag{9.1}$$

The individual characteristics of graduates ***(IND)*** include: gender, age, disability status, ethnicity, subject studied and final grade. Higher education characteristics ***(HEI)*** include a series of dummy variables for the different types of institutions ranging from university belonging to the so-called 'Russell group' (the HEIs which are perceived to be top in the country) to other 'old' universities (i.e. with university status before 1992), to 'new' universities (i.e. polytechnics which gained university status in 1992) and finally colleges.

The model in Eq. (9.1) provides baseline estimation for the wage premium of each migration category non-corrected for selectivity.

To correct for migrant selectivity our second step is a propensity score matching model (for full details on this approach see Caliendo and Kopeinig 2008) in which we treat migration as 'treatment' (we examine each of the four migration groups separately relative to the non-migrant category) and each migrant is matched with a similar individual in the non-migrant category.

Ideally, to correctly evaluate the effect of migration one would want to observe the salary outcome of an individual in the case that he/she migrated (Y_1) and in the case that he/she does *not* migrate (Y_0). However, for each individual we only have one observation, either Y_1 *or* Y_0, depending on their migration decision. As we cannot observe $\Delta Y = Y_1 - Y_0$, we instead settle for matching each migrant with a 'comparable' non-migrant (or a comparable group of non-migrants) and calculate the average treatment effect on the treated (ATT), τ defined as:

$$\tau_{ATT} = E(Y_1|X, d = 1) - E(Y_0|X, d = 1) \tag{9.2a}$$

Or simply

$$\tau_{ATT} = E(Y_1|\, d = 1) - E(Y_0|\, d = 1) \tag{9.2b}$$

where d is the treatment variable and **X** are the other observed characteristics.

Individuals are matched using 'propensity scores' (PS) which are simply the estimated probabilities of having the treatment based on the observed **X** characteristics (calculated by a probit model[4]).

$$PS = pr(d = 1|X) \tag{9.3}$$

[4] Since we have more than one category (four migration strategies) we could have employed a multinomial logit to estimate the migration probabilities but following Lechner (2002) we estimate a series of probits for each pair of migration strategy and non-migration. Using a series of probits instead of a multinomial model in our case leads to better matches in terms of lower standardised bias measures.

Once the propensity scores are calculated, there are several method to match ‘treated’ and ‘untreated’ individuals (also called the ‘control’ group). The most straightforward one is to match each treated individual with the untreated individual with the most similar propensity scores (nearest neighbour matching). Each untreated individual can be used as a match for just one treated individual (matching without replacement) or for more than one (matching with replacement). Matching with replacement is generally preferred because it ensures better matches (reduces bias).

However, more sophisticated ways of matching treated and untreated individuals are also available. For instance, one might decide to match a treated individual to all the untreated individuals with propensity scores within a certain range (radius matching). A ‘tolerance’ level (caliper) is normally set to avoid bad matches. Alternatively, one treated individual can be matched to a weighted average of all the individuals in the control group (i.e. d = 0), where the different weights are assigned based on the propensity scores, i.e. untreated individuals with closer scores to the treated one are given higher weights (Kernel matching). Note that matching is only possible if comparable individuals in the control group exist for those in the treated group, known as the common support, and hence any observations that do not fall into this common support are thrown away. Different matching methods, as seen above, have different ways of defining this common support.

Although some (e.g. Di Cintio and Grassi 2013) believe that Kernel matching is superior to the other methods, there is no definitive answer to which matching method is preferable. Hence, we present the results of all these three possible matching methods and how they compare to the OLS estimates.

Finally, we also present a measure of the ‘goodness’ of the matching between treated and untreated individuals, the so-called ‘measures of standardised bias’ (Rosenbaum and Rubin 1985). This measure compares the standardized biases (SB) before and after the matching as follows:

$$SB_{before} = 100.\frac{\overline{X}_1 - \overline{X}_0}{\sqrt{0.5.(Var_1(X) + Var_o(X))}} \tag{9.4a}$$

$$SB_{after} = 100.\frac{\overline{X}_{1m} - \overline{X}_{0m}}{\sqrt{0.5.(Var_{1m}(X) + Var_{om}(X))}} \tag{9.4b}$$

Values of the standardized bias after the matching of 5 or below are considered indicative of a good matching, with values below 3 showing an excellent match. We acknowledge that PSM may not fully correct for selection effects as there may still be selection on unobservables and hence PSM is only as good as the selection on the observables (variables available) – see McKenzie et al. (2010) for more on this issue. However, we find that our results have very good outcomes in terms of reducing the standardized bias and no more than 1.7 % (a minimum of 0 %) of observations are lost due to not falling in the common support in any of our matching models.

9.5 Results

The first step of our analysis was to estimate a Mincer-type salary equation as in Eq. (9.1). We did that for all our graduates in our sample and then separately for creative and STEM graduates. The results are shown in Table 9.1.

Most results on the individual personal characteristics are in line with expectations. Women are, on average, paid less than men. The disadvantage is even more visible in the science and technology (STEM) sectors – which are traditionally male dominated – while it is less in the more creative professions. In line with the human capital theory, salaries increase with age, with this effect particularly likely at earlier ages with 94 % of our sample under 34, which is often used as a proxy for experience. Also in line with the human capital theory are the results on final grades.[5] Graduates with the best grades (first) command higher salaries when entering the labour market followed by the 'second-best' (two-one). Graduates with lower grades (two-two and third or a pass) have the lowest salaries. Belonging to a black ethnic minority is also a disadvantage, while there is no significant difference between Asians and white graduates (the base category). As for subjects studied, the results also conform to expectations. Subjects allied to medicine graduates are doing well in the labour market and so are graduates in engineering, mathematics, architecture, economics and education. On the opposite side, biological and physical scientists have lower than average salaries and so do graduates in arts and humanities (history, communication, social studies, linguistics, law).

As for the quality of HEIs, graduates from Russell group universities seem to be able to secure a better job than the rest, with an average increase of entry salary of about 4 %. The other 'old' universities, 'new' universities (ex-polytechnics) and college graduates are not statistically different from each other when it comes to graduate entry-job salaries, with the only exception of college graduates doing worse in terms of salaries for creative graduates. This result is somewhat surprising as most colleges are specialized exactly in this kind of courses.

Although the results in Table 9.4 are interesting and provide us with a baseline estimation of the effect of different migration behaviour on entry salaries, they do not take into account the problem of selectivity among migrants. As demonstrated by other contributions (Faggian 2005; Faggian and McCann 2009b) different migration behaviours are associated with different types of graduates. Repeat migrants, for instance, tend to be younger, with a degree from a more prestigious university – preferably in economics, engineering or architecture – and have higher final grades. Non-migrants, at the opposite, are more likely to be older, female, belonging to an ethnic minority and having done more poorly at university. As such, some issues about migrant self-selectivity are evident. Since migration behaviour is affected by institution type, and we have seen that those graduating from different institution

[5] Traditionally UK degrees are measured using the following degree classifications: first, upper second, lower second, third, pass and fail, with a first or a second class degree classified as a 'good degree'.

Table 9.4 Mincer salary-equation results (OLS)

	All graduates	STEM	CREATIVE
Female	−0.037***	−0.045***	−0.022**
	[−11.283]	[−9.081]	[−2.465]
Age (ref: <22)			
Age 22–24	0.043***	0.047***	0.020**
	[12.613]	[8.584]	[2.514]
Age 25–33	0.139***	0.108***	0.139***
	[23.266]	[12.011]	[7.902]
Age 34+	0.201***	0.165***	0.178***
	[20.527]	[13.007]	[7.871]
Disable	−0.012***	−0.016**	−0.007
	[−2.904]	[−2.220]	[−0.858]
Ethnicity(ref: white)			
Black	−0.032***	−0.059***	−0.008
	[−3.440]	[−3.723]	[−0.278]
Asian	−0.019*	−0.028**	0.012
	[−1.871]	[−2.042]	[0.548]
Mixed	−0.005	−0.005	0.026
	[−0.449]	[−0.270]	[1.195]
Other	−0.051***	−0.064**	−0.104**
	[−2.634]	[−2.009]	[−2.513]
Degree class (ref: upper second)			
First class	0.045***	0.059***	0.037***
	[10.484]	[12.616]	[3.973]
Lower second	−0.035***	−0.037***	−0.018**
	[−9.991]	[−7.430]	[−2.315]
Third/pass	−0.056***	−0.065***	−0.049***
	[−7.289]	[−5.569]	[−2.701]
Other degree class	−0.032***	−0.042*	0.05
	[−2.740]	[−1.884]	[1.225]
Subjects			
Subject allied to medicine	0.081***	0.134***	
	[5.538]	[9.494]	
Biological sciences, agriculture and relates subjects	−0.095***		
	[−11.282]		
Physical sciences	−0.045***	0.046***	
	[−4.382]	[5.453]	
Mathematical and computer science	0.060***	0.155***	
	[7.348]	[17.350]	
Engineering and technology	0.102***	0.189***	
	[9.288]	[16.126]	
Architecture, building and planning	0.046**	0.266***	0.101***
	[2.574]	[17.981]	[5.660]
Social studies	−0.028*		
	[−1.943]		
Economics and politics	0.036**		
	[2.497]		

(continued)

Table 9.4 (continued)

	All graduates	STEM	CREATIVE
Law	−0.067***		
	[−6.806]		
Mass communications and documentation	−0.120***		0.035***
	[−10.757]		[3.395]
Linguistics, classics, languages and related subjects	−0.095***		
	[−8.371]		
History and philosophical studies	−0.114***		
	[−12.120]		
Creative arts and design	−0.160***		
	[−19.084]		
Education	0.052***		
	[2.657]		
University type (ref: New university)			
Russell group	0.037***	0.040***	0.016
	[3.895]	[3.431]	[1.078]
Other old	0.003	0.006	0.007
	[0.331]	[0.590]	[0.315]
FE/HE college	−0.007	0.01	−0.030**
	[−0.727]	[0.576]	[−2.315]
Migration category			
Late migrant	0.063***	0.086***	0.032*
	[9.880]	[9.391]	[1.740]
University stayer	0.019***	0.046***	−0.005
	[4.090]	[5.875]	[−0.442]
Return migrant	−0.014***	−0.0001	−0.021*
	[−2.861]	[−0.009]	[−1.938]
Repeat migrant	0.097***	0.126***	0.065***
	[14.463]	[13.176]	[5.149]
Observations	52,792	20,398	6,769
r-squared	0.261	0.262	0.149

t statistics in brackets
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

types on average earn more, it is worth acknowledging that part of the returns to migration we observe may be as a result of the type of institution attended – this is beyond the scope of the chapter but something for future research.

To correct for selectivity biases, we adopt the propensity matching method described in the previous section. First, we calculate propensity scores for each individual (based on the treatment and control groups) in our sample using a probit model. The following characteristics were included in the probit model: gender, age group, ethnicity, course characteristics, degree subject, degree classification, institutional type (Russell group, old, new HEIs and colleges) and region of domicile. Second, we match the individuals in the treatment group to an individual in the control group based on their scores using alternative criteria to make sure our

Table 9.5 Propensity score matching results: control group is the non-migrant category

	% difference in salary			
	OLS	***NN***	***Radius***	***Kernel***
ALL GRADUATES				
Late migrant	6.50***	7.21***	7.70***	7.53***
Stayer	1.92***	2.84***	3.19***	2.67***
Returner	−1.39***	−1.81	−1.37	−1.28
Repeat migrant	10.19***	14.55***	15.23***	14.85***
STEM				
Late migrant	8.98***	8.57***	8.58***	8.81***
Stayer	4.71***	3.58***	5.60***	5.81***
Returner	−0.0001	1.78	0.66	0.61
Repeat migrant	13.43***	15.46***	15.52***	16.29***
CREATIVE				
Late migrant	3.25*	3.82	2.24	3.73*
Stayer	−0.50	1.26	1.60	5.81
Returner	−2.08*	−1.88	−1.01	−0.92
Repeat migrant	6.72***	10.75***	11.53***	10.42***

% differences calculated by taking the exponential and subtracting (Derrick 1984)
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

results are robust to different matching procedures. We start from a simple nearest neighbour matching with replacement (NN) and then move to a radius and Kernel matching approach.[6] Although we have done the matching for each pair of migration alternatives, we only present the results where we match each migration category (the treatment group) to the non-migrant category, the control group (which was also our baseline in the OLS regressions).

As it can be seen from the results in Table 9.5, even after controlling for individual migrant characteristics, repeat migration is associated with a significant salary benefit (around 15 %). Although STEM graduates benefit more from it, the benefit is substantial also for creative graduates (around 10–11 % after the matching).

However, not all sequential migration behaviours are conducive to benefits and this is especially true for creative graduates. While late migration and staying in the university area for work are associated with a salary benefit of around 9 % and 5 % respectively for STEM graduates, there seems to be no substantial gain for creative graduates compared to not migrating at all. This has important implications, as it seems to suggest that the choice of creative graduates is actually dichotomous: either they decide to stick to their original domicile and build connections there or they have to be willing to be highly mobile. Any migration behaviour in between does not bring any additional benefit. This is consistent with the idea that creative graduates have an atypical career (McRobbie 1998; Aston 1999; Comunian et al. 2010), which relies – sometimes heavily – on a network of acquaintances to

[6] We use a caliper of 0.01 for the nearest neighbour and radius matching and a bandwidth of 0.06 for the kernel matching.

Table 9.6 Standardized bias before and after the matching

	Before	NN	Radius	Kernel
STEM				
Late migrant	6.31	2.55	0.84	0.63
Stayer	13.59	2.70	1.93	2.02
Return migrant	13.02	2.92	2.14	2.21
Repeat migrant	17.77	3.69	2.51	3.09
CREATIVE				
Late migrant	8.74	4.55	2.86	1.89
Stayer	12.99	3.40	1.98	1.36
Return migrant	13.04	3.83	1.68	1.52
Repeat migrant	15.46	3.66	2.20	1.99

help establishing a name and become successful in the sector. In this sense, some effects of a one-off migration can be offset by the advantage of not migrating at all and instead establish a network in the original domicile. However, migrating twice (repeat migration) still carries some extra benefits.

Return migration is an interesting case. The descriptive statistics show that return migration is associated with a salary 'penalty' rather than gain. In other words, individuals are worse off being return migrants rather than not migrating at all. Although the results of the PSM are less conclusive on this point, they do show that return migration is worse than any other migration behaviour and, in fact, show there is no statistically significant difference in the level of salaries of return migrants and non-migrants (i.e. people who did not move at all either to study or to work). This is compatible with the idea that return migration is – in most cases – a 'corrective' movement (Davanzo 1976), where graduates go back to their original pre-university domicile either because they have not been as successful as they hoped at university or because they realized family ties are important and outweigh the benefits of a higher salary. This result is not totally surprising given that previous research (Faggian et al. 2007a, b and Faggian and McCann 2009b) have demonstrated that return migrants are indeed graduates with the worst university achievements.

As the quality of the matching is obviously of fundamental importance for our results, we also calculated the before- and after-standardized bias as suggested by Rosenbaum and Rubin (1985). The results (presented in Table 9.6) show that the bias is significantly reduced after the matching and all the values are well below the tolerance level of 5 and – in most cases – even below the lower threshold of 3, confirming the quality of our matching.

9.6 Conclusions

This chapter analyzed the effect of interregional migration on entry salaries of British graduates. Graduates were classified according to their sequential migration behavior first from their pre-university domicile to university and then from university to first job post-graduation.

Our results show that ‘repeat migration’, as expected, is associated with the highest wage premium of about 15 %. Other migration behaviors are also advantageous although differently for different types of graduates. Creative graduates, for instance, do not benefit much from migration behaviors other than repeat migration. STEM graduates, on the contrary, benefit from both late migration (with a wage premium of about 9 %) and staying in the university area to work (with a wage premium of about 5 %).

Return migration is either associated with a wage penalty or – at best – with no statistical effect, showing that in most cases return migration is a corrective movement for UK graduates following an unsuccessful outcome of the previous movement.

The policy implications of these results are quite evident in an era of increasing tuition fees. A recent report by Liverpool Victoria[7] underlines how, faced with the increased burden of paying for their higher education costs, a greater number of students are choosing to live with their parents and attend their local university or – if they do leave to study elsewhere – they then decide to return to their original domicile after study as a means to reduce costs while repaying their student loan. Our research shows that both behaviors could potentially hinder the job opportunities of graduates by reducing their mobility and hence the chances of finding the best job-match possible.

Finally there are several avenues for future research. Firstly examining in more depth how the university type may affect both the decision to migrate and the potential benefit from migration. Secondly we have only focussed on nominal salaries and future research will examine regionally adjusted wage rates and in particular the role of London in the potential benefits of migration.

Appendix

Subject Definitions

The definition of creative subjects was based on the definition used by Faggian et al. (2013). Consistent with previous definitions (Comunian et al. 2010; Abreu et al. 2012; Faggian et al. 2013) creative subjects included all JACS,[8] HESA’s subject coding system, codes starting with W (creative arts and design) and P (mass communication and documentation) plus architecture and landscape design[9] (K1, K3, K9). However, the results of Comunian et al. (2014) suggest that multimedia computer science; software engineering and design students are better

[7] See http://www.lv.com/media_centre/press_releases/university-ghost-towns

[8] JACS is the Joint Academic Coding System used by HESA to classify subjects see http://www.hesa.ac.uk/dox/jacs/JACS_sg.pdf for these codes.

[9] A complete list of these subjects can be found in Comunian et al. (2010).

classified as STEM students rather than creative students, and they are therefore classified under STEM students rather than creative students.

STEM subjects were defined using a definition similar to that of several government reports (BICS 2011; Oxford Economics 2009; UKCES 2011) consisting of:

– Medicine and Dentistry – JACS codes beginning with A
– Veterinary Sciences, Agriculture and Related Subjects – JACS codes beginning with D
– Subjects Allied to Medicine (excluding Nursing) – JACS codes beginning with B (excluding B7)
– Biological Sciences (including Psychology) – JACS codes beginning with C
– Physical Sciences– JACS codes beginning with F
– Technologies – JACS codes beginning with J
– Engineering – JACS codes beginning with H
– Mathematical and Computer Sciences – JACS codes beginning with G
– Built Environment (excluding Planning subjects). – JACS codes beginning with K (excluding K4 and K1, K3, K9 classified as creative subjects)

All subjects not covered by the STEM or creative subject definitions were grouped under 'other' subjects.[10]

References

Abreu M, Faggian A, Comunian R, McCann P (2012) Life is short and art is long: the persistent wage gap between Bohemian and non-Bohemian graduates. Ann Reg Sci 49:305–321

Aston J (1999) Ambitions and destinations: the careers and retrospective views of art and design graduates and postgraduates. Int J Arts Des Educ 18:231–240

Becker G (1993) Human capital: a theoretical and empirical analysis with special reference to education. The University of Chicago Press, Chicago

BICS (2011) STEM graduates in non-STEM jobs, BIS research paper no 21. http://www.bis.gov.uk/assets/biscore/further-education-skills/docs/s/11-770-stem-graduates-in-non-stem-jobs-executive-summary

Borjas GJ (1995) Assimilation and changes in cohort quality revisited: what happened to immigrant earnings in the 1980s? J Labor Econ 13:201–245

Caliendo M, Kopeinig S (2008) Some practical guidance for the implementation of propensity score matching. J Econ Surv 22(1):31–72

Card D (2001) Immigrant outflows, and the local labor market impacts of higher immigration. J Labor Econ 19(1):22–64

Comunian R, Faggian A, Li QC (2010) Unrewarded careers in the creative class: strange case of Bohemian graduates. Pap Reg Sci 89:389–410

Comunian R, Faggian A, Jewell S (2014) Embedding arts and humanities in the creative economy: the role of graduates in the UK. Environ. Plan C (forthcoming)

DaVanzo J (1976) Differences between return and nonreturn migration: an econometric analysis. Int Migr Rev 10:13–27

[10] Note that medicine and dentistry students were omitted, given they are salary outliers and the majority do not have a degree classification.

Derrick FW (1984) Interpretation of dummy variables in semilogarithmic equations: small sample implications. South Econ J 50(4):1185–1188
Détang-Dessendre C, Drapier C, Jayet H (2004) The impact of migration on wages: empirical evidence from French youth. J Reg Sci 44(4):661–691
Di Cintio M, Grassi E (2013) Internal migration and wage differentials among Italian university graduates. Pap Reg Sci 92(1):119–140
Faggian A (2005) Human capital, migration and local labour markets: the role of the higher education system in Great Britain. Ph. D. Thesis, University of Reading
Faggian A, McCann P (2009a) Human capital, graduate migration and innovation in British regions. Camb J Econ 33:317–333
Faggian A, McCann P (2009b) Universities, agglomerations and graduate human capital mobility. J Econ Soc Geogr (TESG) 100(2):210–223
Faggian A, McCann P, Sheppard S (2006) An analysis of ethnic differences in UK graduate migration behaviour. Ann Reg Sci 40(2):461–471
Faggian A, McCann P, Sheppard S (2007a) Human capital, higher education and graduate migration: an analysis of Scottish and Welsh students. Urban Stud 44(13):2511–2528
Faggian A, McCann P, Sheppard S (2007b) Some evidence that women are more mobile than men: gender differences in UK graduate migration behaviour. J Reg Sci 47:517–539
Faggian A, Comunian R, Jewell S, Kelly U (2013) Bohemian graduates in the UK: disciplines and location determinants for entering creative careers. Reg Stud 47(2):183–200
Gallaway LE (1969) The effect of geographic labor mobility on income: a brief comment. J Hum Resour 4:103–109
Greene WH (2000) Econometrics, 4th edn. Prentice Hall, New York
Greenwood MJ (1975) Research on internal migration in the United States: a survey. J Econ Lit 13(2):397–433
Greenwood MJ, Hunt G, Kohli U (1996) The short-run and long-run factor-market consequences of immigration to the United States. J Reg Sci 36(1):43–66
Ireland N, Naylor R, Smith J, Telhaj S (2009) Educational returns, ability composition and cohort effects: theory and evidence for cohorts of early-career UK graduates, Warwick economic research papers. University of Warwick, Coventry
Jayet H (1996) L’analyse économique des migrations: une synthèse critique. Rev Economique 47:193–226
Jewell S (2008) Human capital acquisition and labour market outcomes in UK higher education. School of Economics. University of Reading, Reading
Kennan J, Walker J (2011) The effect of expected income on individual migration decisions. Econometrica 79(1):211–251
Lansing JB, Morgan JN (1967) The effect of geographical mobility on income. J Hum Resour 2:449–460
Lechner M (2002) Some practical issues in the evaluation of heterogeneous labour market programmes by matching methods. J R Stat Soc A 165:59–82
Lehmer F, Möller J (2008) Group-specific effects of inter-regional mobility on earnings - a microdata analysis for Germany. Reg Stud 42:657–673
McKenzie D, Stillman S, Gibson J (2010) How important is selection? experimental vs. non-experimental measures of income gains from migration. J Eur Econ Assoc 8(4):913–945
McRobbie A (1998) British fashion design: rag trade or image industry? Routledge, London
Mincer J, Jovanovic B (1979) Labor mobility and wages, NBER working paper no 357. National Bureau of Economic Research, Cambridge, MA
Nakosteen RA, Westerlund O (2004) The effects of regional migration on gross income of labour in Sweden. Pap Reg Sci 83(3):581–595
Nakosteen RA, Zimmer MA (1982) The effects on earnings of interregional and interindustry migration. J Reg Sci 22:325–341

Naylor R, Smith J, Mcknight A (2007) Sheer class? Returns to educational performance: evidence from UK graduates' first destination labour market outcomes, Warwick economic research papers. University of Warwick, Coventry

Ottaviano GIP, Peri G (2005) Rethinking the gains from immigration: theory and evidence from the U.S., vol 11672, NBER working paper. National Bureau of Economic Research, Cambridge, MA

Oxford Economics (2009) Forecasting future skill needs in Northern Ireland, report for the Department of Learning and Employment in Northern Ireland. http://www.delni.gov.uk/del_future_skill_needs_final_report_june_09_v4_no_links.pdf

Rosenbaum P, Rubin D (1985) Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. Am Stat 39(1):33–38

Sabot RH (1987) Internal migration and education. In: Psacharopoulos G (ed) Economics of education research and studies. Pergamon Press, Oxford, pp 196–197

Shierholtz H (2010) Immigration and wages: methodological advancements confirm modest gains for native workers. Economic policy institute briefing paper no 255. Economic Policy Institute, Washington, DC

Sjaastad L (1962) The costs and returns of human migration. J Polit Econ 70(Suppl):80–93

UKCES (2011) The supply and demand for high level STEM skills, briefing paper. http://www.ukces.org.uk/assets/ukces/docs/publications/briefing-paper-the-supply-of-and-demand-for-high-level-stem-skills.pdf

Yankow J (2003) Migration, job change, and wage growth: a new perspective on the pecuniary return to geographic mobility. J Reg Sci 43:483–516

Part III
Spatial Systems and Economic Development

Chapter 10
Intraregional Income Convergence: Cross Section and Time Series Evidence from the USA

Stilianos Alexiadis, Konstantinos Eleftheriou, and Peter Nijkamp

10.1 Introduction

The publication of the ground breaking work of Baumol (1986) was the spark that ignited an enormous interest to the issue of convergence in per capita income (e.g. Aghion and Howitt 1998; Baldwin et al. 2003; Capello 2006; Le Gallo 2004; Overman and Puga 2002; Ioannides and Overman 2004; Li and Haynes 2010). As perhaps anticipated, there is a growing number of attempts to assess regional convergence using extensive datasets, such as the regions of the European Union (e.g. Button and Pentecost 1995; Cuadrado-Roura et al. 1999; Rodríguez-Pose 2001; Rodríguez-Pose and Fratesi 2004; Lopez-Bazo et al. 2004; Alexiadis and Tsagdis 2010), the US states (e.g. Christopoulos and Tsionas 2007; Checherita 2009) and the regions of individual countries (e.g. Rodríguez-López et al. 2009; Hierro and Maza 2010). Most of the literature concerning convergence has been developed in terms of per-capita income using cross-section data. Nevertheless, convergence is by no means a mechanical phenomenon, which happens everywhere and always (Cuadrado-Roura 1996, p. 47). Regional convergence is characterised by rapid transformations and adjustments, properties that are difficult to be examined in a cross-section context. This has led to the development of alternative

S. Alexiadis (✉)
Department of Agricultural Policy & Documentation, Division of Agricultural Statistics, Room 501, Ministry of Rural Development & Foods, 5 Acharnon Street, 101 76 Athens, Greece
e-mail: ax5u010@minagric.gr

K. Eleftheriou
College of Business Administration, Abu Dhabi University, Abu Dhabi Campus, P.O. Box 59911, Abu Dhabi, United Arab Emirates
e-mail: k.eleftheriou@adu.ac.ae

P. Nijkamp
Department of Spatial Economics, VU University, De Boelelaan 1105, 1081 HV Amsterdam, The Netherlands
e-mail: p.nijkamp@vu.nl

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methodologies based on cointegration analysis generating a considerable amount of empirical literature (e.g. Bernard and Jones 1996; Carlino and Mills 1993; Sun et al. 2010).[1] Still, the crucial question of the adjustment towards steady-state equilibrium, which lies at the heart of the convergence debate, remains unanswered. An approach to this issue can be provided through an Error-Correction-Model (hereafter ECM). Recent years have witnessed a growing number of attempts to implement this model to examine the evolution of regional employment and unemployment (e.g. Baddeley et al. 1998, 2000; Martin and Tyler 2000; Gray 2004; Hunt 2006; Alexiadis and Eleftheriou 2010).

While the ECM offers a thorough perspective to the aforementioned issue, the question of long-run income convergence has remained, to our knowledge, a rather unexplored area. This is perhaps not so surprising given that steady-state equilibrium is easily defined in the case of employment or unemployment in which the national level is considered (e.g. Martin 1997; Keil 1997; Gray 2005). Such a definition is not so clear when income convergence is the main objective of the analysis. It becomes of crucial importance, therefore, to determine a suitable proxy for steady-state equilibrium.

Average per-capita income at the national level seems to be a good candidate. Nevertheless the implied social preferences cannot be captured by such a proxy. A 'convergence-perspective' taken by society does not coincide necessarily with movements towards an average, whereas a relatively high level of per-capita income might reflect those preferences in a more realistic manner. Seen in this light, a geographical unit with the highest level of per-capita income, within a given set of areas with close proximity, might constitute an appropriate proxy for steady-state equilibrium.

Although, cross section analysis is also applied, our chapter goes beyond this 'conventional' approach. Using the ECM, as a point of departure, the hypothesis that the US states move towards alternative steady-state equilibria, expressed in terms of the State with the highest per-capita income in the Bureau of Economic Analysis (BEA) region (hereafter HISR), is examined empirically. In that sense this chapter fills an important gap as the empirical assessment of convergence in regional incomes using an ECM model has not so far received due attention.

Divided into four sections, the rest of this chapter is structured as follows. Section 10.2 sets the appropriate framework which the empirical analysis will be conducted upon. The econometric application takes place in Sect. 10.3, in conjunction with a detailed presentation of the obtained results. Finally, a fourth section concludes the chapter and suggests avenues for future research.

10.2 The Empirical Setting

The last 30 years have witnessed a significant upsurge in regional growth and convergence, although not in a uniform path. Some brief comments on this topic will set the scene for what follows. Several distinct types of convergence have been

[1] This kind of analysis has also been implemented in contexts other than regional convergence (e.g. Angulo et al. 2001).

suggested in the literature, each being analysed by distinct groups of scholars employing different methods.[2] Broadly speaking, these methods appear either as cross-section or time-series estimates.

The former is encapsulated in the notion of absolute β-convergence. As a rough-and-ready definition, absolute convergence requires that 'poor' regions grow faster than 'rich' ones; an expectation rooted to the neoclassical model of regional growth. Hurst et al. (2000) offer a lucid explanation of the convergence property: 'Arbitrage possibilities arising from competition and factor mobility were expected to induce a more than average growth performance in lagging regions. Having the economic engine in a higher gear would eventually make these regions reach the standard of living realised elsewhere.' (p. 9). Assuming that income per-capita ($E_{i,T}$) grows as $E_{i,T} = e^{g_{i,T}} E_{i,0}$ and $g_{i,T} = f(E_{i,0})$, then it is possible to express this argument in terms of a regression equation as follows:

$$g_{i,T} = c + bE_{i,0} + \upsilon_i \tag{10.1}$$

where $E_{i,0}$ is the natural logarithm of per-capita income at some initial time for the ith region, $g_{i,T}$ measures the growth rate over a given time interval (T), c is a constant, b is the convergence coefficient and υ_i is the random error-term with the usual properties. [3]

Equation 10.1 is an essential expression for empirical assessments of regional convergence in a cross section context. Despite its simplicity, its implications are quite deep. Absolute convergence requires that $b \in [-1 \quad 0]$.[4] The analytical aspect of this problem can be described as follows. If $b = 0$, then $g_{i,T} = c$, i.e. regions grow at a given rate which can be considered as an indication of an autonomous growth rate that maintains income differences across regions. There is, of course, the case

[2] In this context, some remarks by Martin (1999, p. 73) are highly pertinent: '[T]he focus on long-run income convergence merely revives a theme that was first examined [...] in the classic works by Borts and Stein (1964) and Williamson (1965)'. For useful reviews of the growth-convergence issue see Rogers (2003) and Islam (2003).

[3] Lichtenberg (1994, p. 576) offers an alternative description of the convergence hypothesis: $\frac{d[\mathrm{var}(\ln Y_t)]}{dt} < 0$, where Y_t is labour (or total-factor) productivity at time t and var( ) denote the variance across economies. When there are only two time periods, indexed by 0 and 1, the hypothesis may be expressed as $[\mathrm{var}(\ln Y_0)]/[\mathrm{var}(\ln Y_1)] > 1$.

[4] Equation 10.1 can be enhanced by adding variables to account for technological and structural characteristics. In this case convergence is conditioned upon those characteristics. For example, Barro and Sala-i-Martin (1991) use an index of sectoral mix in several of their regressions, with the explicit aim to control for asymmetric shocks across economies. Paci and Pigliaru (1997) point out how the observed productivity convergence across the Italian regions is indeed generated by a strong process of structural change. Structural change can be regarded as a process that is altering traditional patterns of growth and provoking significant changes in regional disparities, as well as greater diversity in the patterns of development (Rodríguez-Pose 1999). This implies that convergence-dynamics can be examined more thoroughly using Markov chain models. For a more general treatment, together with an empirical application in the context of the EU regions, see Fingleton (1997).

when $b = -1$, which Romer (1996) describes as 'perfect convergence', while $b = 1$ can be conceived as 'perfect divergence'.

An intrinsic distinction is made in the literature between the convergence coefficient b and the speed of convergence β. Following Barro and Sala-i-Martin (1992a) $b = -(1 - e^{-\beta T})$, where T is the number of years included in the period of analysis. The term for $\beta = -\ln(b + 1)/T$ indicates the speed at which economies approach the steady-state value of per capita income over a given time period, i.e. the average rate of convergence. It is possible to state quite generally what the process of convergence entails. If $b < 0$ then $\beta > 0$; a higher β, thus, corresponds to more rapid convergence.

Employing Eq. (10.1) using various data sets, Sala-i-Martin (1996) estimates a 'surprisingly' similar rate of convergence across both regional and national economies, and forms the 'mnemonic rule' that 'economies converge at a speed of about 2 % per year.' (p. 1326).[5]

However, several criticisms have been raised against the conclusions, which this approach has yielded due to the problem known as 'Galton's fallacy' (e.g. Bliss 1999; Cannon and Duck 2000).[6] This is equivalent to a regression towards the mean, leading to a biased estimate of b. All-in-all, cross-section tests are useful as a normative framework, but appear to be inherently unsuited for assessing the dynamic nature of regional convergence. As a result, many economists are searching for an alternative way forward, namely tests of time-series or *stochastic* convergence. Intuitively, convergence between time series will occur when the difference between them becomes arbitrarily small over time or, alternatively, when the probability that the series will differ by more than some specified amount becomes arbitrarily small (Neven and Gouyette 1995).

Time series tests generate robust estimates[7] of the underlying tendencies of convergence within a set of economies[8]. Advocates of this approach (e.g. Bernard

[5] This means that on average, 2 % of the gap in income per capita between two regions is eliminated so that it takes more than 30 years to eliminate one half of the initial gap in per capita incomes.

[6] A simple example by Elster (1989) will illustrate what is meant by 'Galton's fallacy' and the problems to which this mode of thinking can lead. 'The Israeli air force at one time noted that, when pilots were criticized after a bad performance, they usually did better next time. When praised for a good performance, they tended not to do as well on the next occasion. The instructors concluded that criticism is effective in training pilots, [. . .]. They were not aware of the simple statistical principal that a very good performance is on average followed by a poorer one, while a bad performance is on average followed by a better one' (p. 39). Boyle and McCarthy (1999) propose a methodology to test for β-convergence that overcomes this bias. This methodology implements a Kendall's measure of rank concordance (γ-convergence).

[7] Of course, there is an alternative test using panel-data. Examples of this line of research include Badinger et al. (2004), Di Liberto et al. (2008), Esposti and Bussoletti (2008) among others.

[8] In terms of the existing literature, regional studies concentrate to a large extent on the US; the reader interest in these issues can, for instance, refer to the contributions of Carlino and Mills (1993), Tsionas (2000), to name but a few. Empirical studies of stochastic convergence have also been conducted for the regions of the UK (McGuinness and Sheehan 1998) and Greece (Alexiadis and Tomkins 2004).

and Jones 1996; Bernard and Durlauf 1995) claim that convergence is, by definition, a dynamic concept that cannot be captured by cross-sectional studies. In order to shed some light on this issue, an ECM is applied.

A time series, let $\{X_t; t = 1, 2, \ldots\}$, is stationary if the following conditions are met. First, constant mean and variance over time[9] and second, the (auto) co-variances between two different points in time, let t and s, depends only on the absolute difference between them ($|t - s|$).[10] If one of the above conditions does not hold, then the time-series in question is non-stationary. Of course, non-stationary series can become stationary by differencing them up to the point where the above conditions hold. The number of times that non-stationary series are required to be differenced, as to become stationary, defines the order of integration. This can be determined, for instance, through the test proposed by Dickey and Fuller (1981). [11] In most cases, economic time-series have been found to be integrated of order one, i.e. $I(1)$.

Despite the fact that several time series can be characterized as non-stationary, it is possible that certain combinations among these series exhibit a common behaviour over time. In other words, a (linear) combination of non-stationary series might be integrated of a lower order than the individual series themselves, leading to what is known as cointegration (Engle and Granger 1987).

The following example is illustrative. Let X_t and Y_t, denote two time-series of $I(1)$, with the long-run equilibrium relationship:

$$Y_t = \beta_0 + \beta_1 X_t \tag{10.2}$$

Deviations from long-run equilibrium can be calculated as

$$u_t = Y_t - \beta_0 - \beta_1 X_t \tag{10.3}$$

If the two time-series are cointegrated, then it is necessary the deviations to be integrated in an order lower than that of the individual series, i.e. $I(0)$. The test for cointegration involves three steps (Engle and Granger 1987). First, through a unit root test, e.g. an Augmented Dickey Fuller (henceforth ADF) test, the order of integration between the two time-series is determined. Second, the residuals ($\hat{u}_t$) from regressing Eq. 10.2, the cointegrating regression, are estimated. Third, an ADF test is applied to specify the order of integration of $\hat{u}_t$.[12]

Having determined the cointegration property, the short-run adjustment process can be examined in terms of an ECM:

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[9] $E(X_t) = \mu$ and $Var(X_t) = \sigma^2 < \infty$.

[10] $Cov(X_t, X_s) = \sigma_{|t-s|}$ $(t \neq s)$.

[11] Phillips and Perron (1988) propose an alternative test.

[12] Given that the obtained residuals are derived from the original time-series, the critical values given by Dickey and Fuller (1981) are inappropriate. Instead the relevant critical values for this test can be found in MacKinnon (1996).

$$\Delta Y_t = \theta \hat{u}_{t-1} + a_0 + a_1 \Delta X_t + \varepsilon_t \tag{10.4}$$

where Δ denotes the first difference, i.e. $\Delta Y_t = Y_t - Y_{t-1}$, and ε_t is a random residual series.

In Eq. (10.4) $\hat{u}_{t-1}$ is the error correction term which captures the adjustment towards the long-run equilibrium (steady-state relationship) between Y_t and X_t. Of critical importance is the parameter θ, which provides an estimate of the speed of adjustment. More specifically, this parameter indicates the proportion of the dis-equilibrium between Y_t and X_t that is corrected in the next period. Typically, one would expect that parameter $\theta < 0$. The argument runs as follows. Assuming that Y was below its equilibrium level in period $t-1$ (so that $\hat{u}_{t-1} < 0$), then Y_t needs to be increased $(\Delta Y_t > 0)$ in an attempt to achieve equilibrium, implying that $\theta < 0$.

Yet, economic knowledge cannot be gleaned from theory alone. For theoretical innovations to convince, they need to be evaluated through observed facts. We shall submit the empirical context to econometric tests and then, we shall discuss the main findings.

10.3 Per-capita Income Convergence Across the US States

Regional growth may be convergent or divergent. It is the purpose of this section to provide an assessment of whether or not convergence is apparent across the 49 states of the US.[13] Although the bulk of the subsequent analysis is focused on stochastic convergence, nevertheless, some tentative evidence using simple measures of regional convergence, such as σ-convergence and absolute β-convergence, are necessary.

The simplest approach to testing for convergence is to examine changes in the coefficient-of-variation (σ-convergence).[14] This test[15], when carried out for the 49 states over the period 1929–2005, produces the outcome shown in Fig. 10.1.

Over the examined period the long-run trend in the coefficient-of-variation suggests σ-convergence, although at the beginning of the period some increases are observed. The conclusion to be drawn, therefore, on the basis of the σ-convergence test alone is that the states of the US have moved closer together as a group since the dispersion of income per-capita at the end of the period is narrower than at the beginning. However, the coefficient-of-variation is only a simple descriptive tool and is not based on a model of regional convergence. The

[13] Owing to the lack of data, Alaska and Hawaii had to be omitted, since the datasets for these states begin at 1950.

[14] σ-convergence is said to be present if the dispersion of income per capita (or worker) across countries, measured by some convenient measure of dispersion (such as the standard deviation or the coefficient-of-variation), display a tendency to decline through time (Dalgaard and Vastrup 2001, p. 283).

[15] The source for our data is the US Bureau of Economic Analysis.

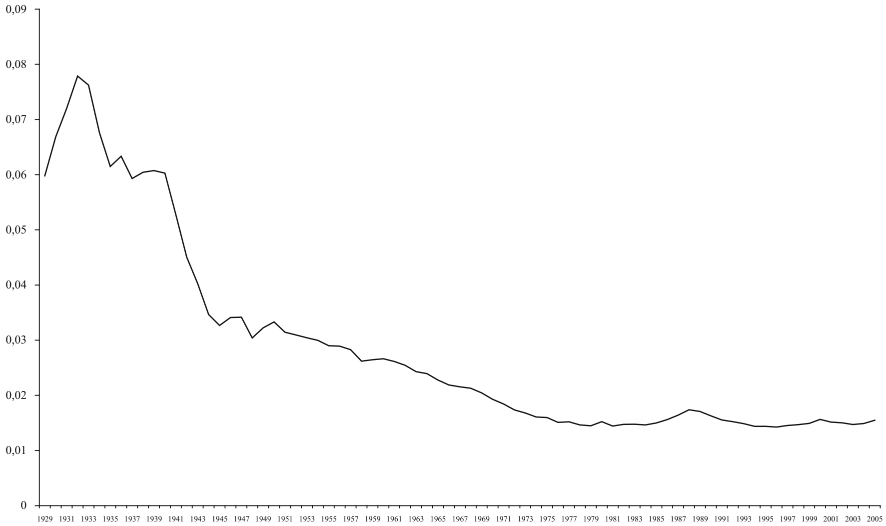

Fig. 10.1 Coefficient-of-variation: 49 US states: 1929–2005

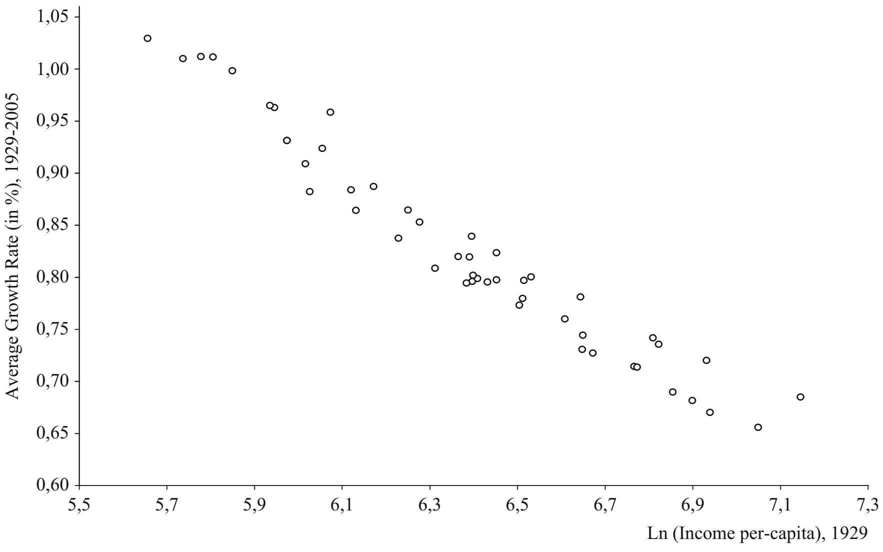

Fig. 10.2 Absolute convergence, 49 US states: 1929–2005

concept of β-convergence is derived from the standard neoclassical model and is examined next.

The potential for β-convergence is indicated in Fig. 10.2, which shows a scatterplot of the average annual growth rate against the initial level of per-capita income. Prior to the formal convergence test, casual inspection of the data in

Table 10.1 Absolute β-convergence and the speed of convergence: US states, 1929–2005

OLS, Estimated equation: $g_i = c + by_{i,\theta}$		
c	8.3217*	(34.702)
b	−0.6714*	(−18.356)
Implied β	1.4456*	(−18.022)

Notes: Figures in brackets are t-rations. An asterisk (*) indicates statistical significance at 95 % level of confidence. The rate of convergence is defined as $\beta = -\frac{\ln(b+1)}{T}$

Fig. 10.2 provides a clear indication of an inverse relationship between the average annual growth rate and initial level of income per-capita.

The presence of β-convergence, however, cannot be confirmed by visual inspection alone. Therefore, the cross-section test, based on estimation of Eq. (10.1) for the 49 US States, is applied to the period 1929–2005. The results, presented in Table 10.1, show the convergence coefficient (b) to be negative and significant.

The presence of absolute convergence in the form of a negative relationship between the rate of growth and initial per-capita income is suggested by this evidence, and the US states have, on average, shown a strong tendency towards 'perfect convergence' over the period 1929–2005, at a rate of 1.4 % per annum.

The implications of estimating a rate for regional convergence are far-reaching. For our purposes, however, one particular consequence is of the utmost importance. The most popular interpretation of the convergence parameter seems to be that it reflects the operation of diminishing returns to scale in reproducible factors. Barro and Sala-i-Martin (1992a, b) and Mankiw et al. (1992), for example, interpret their empirical results within the framework of a 'conventional' neoclassical model with exogenous technical progress.[16] This allows them to explicitly relate the rate of convergence to the coefficients of the aggregate production function and other structural parameters.[17] A slow rate of convergence, thus, might be interpreted as an indication that the production technology exhibits almost constant returns to scale in reproducible factors. This contention seems much more plausible when a broad capital aggregate is taken into consideration instead of interpreting capital in

[16] An argument put forward by Solow (1956, 1957), and all theorists in the neoclassical tradition have accepted.

[17] Using data on output (GDP) per head for 141 NUTS-2 regions of Europe over the period 1980–1989 Neven and Gouyette (1995) provide two stylized facts. First, the process of convergence among the European regions is far from stable, even if differences in industrial structure is taken into account, and it tends to slow down in the late part of the 1980s. Second, it seems that northern European regions, after a period of stagnation in the early 1980s, converge strongly after 1985, at a time when southern European regions lagging, following a period of rapid convergence in the early 1980s. Neven and Gouyette (1995) estimate a low beta coefficient for the later part of 1980s (unconditional β = 0.251 and conditional with country dummies β = 2.01 for 1980–1985 while over the period 1985–1989 unconditional β = 0.77 and conditional with country dummies β = 0.42). According to their interpretation, this reflects a relative decline of agricultural activities and heavy industries which were concentrated in the poorer regions of the Community. Martin (1998) using a dataset for 104 European regions over the period between 1978 and 1992 estimates that about 1.28 % of the initial gap between regions is eliminated each year.

a restrictive fashion as the sum of the stocks of equipments and structures.[18] A final point deserves notice at this juncture. According to Cheshire and Carbonaro (1995), the detection of β-convergence is simply a sign that the data are not inconsistent with neoclassical theory, and not a direct test of diminishing returns to capital or of the income equalising consequences of factor mobility.

Regional convergence is, by definition, a dynamic concept. This clearly implies the need for more detailed and focused analysis, which can be obtained by assessing stochastic or time series convergence.

As demonstrated in Sect. 10.2, the ECM is an appropriate tool for examining long-run relationships between time-series, with the additional advantage of providing an estimate for the rate at which the adjustment process takes place. This model has implemented extensively in analysing regional disparities in terms of unemployment in which the national rate approximates the steady-state. Such an approach inevitably leads to different patterns in the convergence behaviour of regions. This is not, perhaps, surprising since unemployment rates differ between regions due to differences in regional endowments (e.g. population, resources, etc). It is reasonable to assume that those differences affect not only unemployment, but also, and perhaps to a greater extent, income differences, providing thus ample justification for using an ECM.

How, then, an appropriate proxy for steady-state equilibrium can be defined? While the level of per-capita income at national level seems to be a good candidate, nevertheless, does not take into account local spillovers generated by geographical proximity. National per-capita income is, essentially, a weighted average of all the local economies in a country. Such a measure ignores the fact that spillovers diffuse relatively faster towards neighbouring areas rather than to the nation as a whole.

Seen in this light, the process of income convergence implied by the ECM would be more pronounced within a set of localities with close geographical proximity (physically contiguous localities). Consequently, the locality with the highest income[19] in this set is chosen to approximate steady-state equilibrium. In this case the adjustment process would be faster since it is enhanced by geographical proximity, avoiding thus any downward biases imposed by the national level proxy.[20]

[18] Mankiw et al. (1992) provide empirical support for this view using and extension of the Solow model that incorporates human capital as a factor of production (de la Fuente 2002). Although this analysis is admittedly much less based on the 'conventional' neoclassical model, the 'ghost' of diminishing returns still lurks in the background.

[19] Nevertheless, one should bear in mind that a high level of per capita output in a region does not imply that a household or individual is rich. It is average output that is large, and household income depends, first, on whether the income associated with a region's output of goods and services accrues to the region's inhabitants, and second, on the personal distribution of income within the region (Dunford 1993).

[20] Spatial effects can be approximated in various ways. Quah (1996), for example, examining spatial clusters across Europe, normalises per-capita income in a region by the average of all the physically surrounding regions. This approach, however, it is difficult to be applied in an ECM.

Although a considerable part of the empirical literature in regional convergence is confined to the use of total labour productivity, in this chapter convergence is examined in terms of per-capita income. Due to the availability of data for the US States, the exercise covers the period 1929–2005. This data set allows one to examine the relative movements in per-capita income across the geographical units of the US in some detail. The regional groupings used are those delineated by the Bureau of Economic Analysis (BEA). In doing so, we implement an ECM in which the State with highest per-capita income in each BEA Region approximates steady-state equilibrium.

It is possible (and necessary given the concerns of this chapter) to reconstruct a more precise account of the nature of the ECM, especially in terms of steady-state equilibrium. Thus,

$$\Delta y_{it} = a_{i0} + a_{i1}\Delta y_{HISR_t} + \theta_i[y_{i_{t-1}} - (\beta_{i0} + \beta_{i1}y_{HISR_{t-1}})] + \varepsilon_{it} \tag{10.5}$$

where i denotes a given state in a BEA Region, y is the natural logarithm of per-capita income and the subscript HISR stands for the state with the highest per-capita income in each BEA Region. In choosing the appropriate HISR in each BEA Region, the average per-capita income was utilised.[21] Following the discussion in Sect. 10.2, the parameter θ measures the adjustment rate or to which extend the gap between a state's per-capita income and per-capita income in HISR in one period is corrected in the next period.

It is not uncommon in empirical studies of stochastic convergence across the BEA Regions (e.g. Tsionas 2001) to introduce structural breaks. While the absence of them might constitute a criticism to our approach, nevertheless the primary question to be tackled is intraregional convergence[22] and not interregional convergence, as in previous studies.

In order to illustrate these ideas further, it is useful to focus upon Eq. (10.5). In doing so, it is important to spell out that the available time-series are tested for cointegration using the methodology proposed by Engle and Granger (1987).

According to the ADF and Phillips-Perron (PP) tests, all the states are $I(1)$ for 1 % level of significance, with the exemption of the state of Idaho, where only the ADF test does not reject the hypothesis of the first difference non-stationarity. Following this process, an ADF test is conducted for unit-root in the estimated residuals obtained from the cointegrating equation. Expressing this in terms of a regression equation we get the following relationship:

$$y_{it} = \beta_{i0} + \beta_{i1}y_{HISR_t} \tag{10.6}$$

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[21] More technically, $\max\{\bar{y}_i | i \in j\}$, where $\bar{y}_i = \frac{\sum_{t=1}^{m} y_{it}}{m}$ with $j = 1, \ldots, 8$ denoting each BEA Region and m is the number of years included in the empirical analysis.

[22] The term 'intraregional' is used to indicate the behaviour of States within a broad region, i.e. a BEA region, and not Metropolitan Areas.

Table 10.2 Income convergence, US states, 1929–2005, ECM

	ADF test	β_{i0}	β_{i1}	θ_i	a_{i1}	Ramsey-RESET test (p value)
Region 1(Far West) HISR: California						
Neveda	−0.505***[0]	0.093**(0.043)	0.988***(0.005)	−0.532***(0.159)[a]	1.125***(0.168)	0.048
Oregon	−2.460 [1]	−0.534***(0.052)	1.040***(0.006)	−0.151***(0.063)[a]	1.166***(0.062)	0.164
Washington	−2.774*[1]	−0.534***(0.052)	1.040***(0.006)	−0.147**(0.062)[a]	1.165***(0.056)	0.371
Region 2 (Great Lakes) HISR: Illinois						
Indiana	−3.384***[0]	−0.519***(0.043)	1.038***(0.005)	−0.275***(0.055)[b]	1.206***(0.055)	0.057
Michigan	−4.823***[1]	−0.153***(0.35)	1.001***(0.004)	−0.463***(0.092)[a]	1.244***(0.058)	0.014
Ohio	−5.400***[2]	−0.155***(0.023)	1.004***(0.003)	−0.395***(0.075)[b]	1.105***(0.035)	0.138
Wisconsin	−2.849*[10]	−0.541***(0.024)	1.044***(0.030)	−0.343***(0.125)[a]	1.029***(0.070)	0.039
*Region 3 (Mideast)*HISR: District-of-Columbia						
Delaware	−1.595 [0]	−0.15 (0.096)	−0.983***(0.011)	−0.091 (0.065)[a]	1.051***(0.228)	0.021
Maryland	−1.997 [1]	−0.903***(0.102)	1.078***(0.012)	−0.025 (0.043)	0.966***(0.113)	0.219
New Jersey	−2.218 [1]	−0.649***(0.100)	1.059***(0.011)	−0.032 (0.046)[b]	0.991***(0.188)	0.045
New York	−2.707*[2]	−0.224***(0.79)	1.010***(0.009)	−0.061 (0.052)[b]	0.941***(0.237)	0.005
Pennsylvania	−2.210 [2]	−0.784***(0.109)	1.053***(0.012)	−0.047 (0.059)[b]	1.067***(0.236)	0.035
Region 4 (New England) HISR: Connecticut						
Maine	−3.286**[1]	−0.539***(0.037)	1.012***(0.004)	−0.235**(0.101)[a]	0.929***(0.072)	0.534
Massachusetts	−3.482**[1]	−0.199***(0.031)	1.007***(0.003)	−0.234***(0.054)[a]	0.764***(.029)	0.060
New Hamsphire	−3.678***[1]	−0.682***(0.034)	1.046***(0.004)	−0.169**(0.066)[b]	0.843***(0.078)	0.001
Vermont	−2.155 [0]	−0.744***(0.041)	1.037***(0.005)	−0.105**(0.053)	0.922***(0.043)	0.019
Rhode Island	−2.530 [0]	0.078***(0.029)	0.964***(0.003)	−0.139**(0.066)[a]	0.813***(0.030)	0.760
Region 5 (Plaines) HISR: Missouri						
Kansas	−2.667*[0]	−0.373***(0.051)	1.043***(0.006)	−0.257***(0.053)[b]	1.349***(0.075)	0.498
Minnesota	−4.212***[0]	−0.266***(0.022)	1.038***(0.002)	−0.388***(0.101)[b]	1.028***(0.046)	0.178
Iowa	−2.744*[1]	−0.145***(0.049)	1.015***(0.006)	−0.553***(0.127)[b]	1.410***(0.067)	0.312
Nebraska	−4.630***[0]	−0.289***(0.046)	1.033***(0.005)	−0.467***(0.135)[b]	1.251***(0.066)	0.108
North Dakota	−3.040**[0]	−0.930***(0.122)	1.092***(0.015)	−0.316***(0.063)[b]	1.671***(0.173)	0.121
South Dakota	−3.557***[0]	−0.876***(0.097)	1.085***(0.012)	−0.379***(0.093)[b]	1.729***(0.123)	0.116

(continued)

Table 10.2 (continued)

	ADF test	β_{i0}	β_{i1}	θ_i	a_{i1}	Ramsey-RESET test (p value)
Region 6 (Rocky Mountains) HISR: Wyoming						
Idaho	−3.881***[4]	−0.285***(0.055)	1.012***(0.007)	−0.580**(0.242)[b]	1.076***(0.154)	0.628
Montana	−2.870*[1]	0.074*(0.039)	0.977***(0.005)	−0.411***(0.118)[b]	1.001***(0.040)	0.684
Utah	−3.130**[0]	−0.192***(0.046)	1.000***(0.005)	−0.245**(0.095)[a]	0.924***(0.107)	0.776
Colorado	−2.891*[0]	−0.404***(0.042)	1.048***(0.005)	−0.282***(0.070)	0.838***(0.055)	0.119
Region 7 (South East) HISR: Florida						
Arkansas	−2.882*	1.068***(0.051)	1.086***(0006)	−0.206***(0.090)[b]	1.103***(0.099)	0.057
Alabama	−2.437 [3]	−0.996***(0.049)	1.084***(0.006)	−0.218*(0.076)[a]	1.134***(0.099)	0.128
Georgia	−2.140 [0]	−0.802***(0.041)	1.075***(.005)	−0.095*(0.055)[a]	1.001***(0.068)	0.309
Kentucky	−2.587 [0]	−0592***(0.044)	1.043***(0.005)	−0.165***(0.053)[b]	1.017***(0.103)	0.061
Louisiana	−2.838*[1]	−0.331***(0.040)	1.015***(0.005)	−0.173**(0.071)	0.963***(0.060)	0.611
Mississippi	−3.265**[0]	−1.321***(0.055)	1.104***(0.007)	−0.293***(0.104)[a]	1.310***(0.139)	0.224
North Carolina	−3.067**[0]	−0.798***(0.040)	1.072***(0.005)	−0.179*(0.105)[a]	0.981***(0.111)	0.069
South Carolina	−3.143**[0]	−0.994***(0.048)	1.084***(0.006)	−0.153*(0.083)[a]	1.006***(0.104)	0.160
Tennessee	−2.639*[3]	−0719***(0.031)	1.062***(0.004)	−0.226**(0.103)[a]	1.057***(0.101)	0.003
Virginia	−4.171***[1]	−0.402***(0.032)	1.047***(0.004)	−0.252**(0.105)[a]	0.835***(0.125)	0.101
West Virginia	−3.798***[2]	−0.047 (0.033)	0.979***(0.004)	−0.283***(0.081)[a]	0.902***(0.105)	0.001
Region 8 (South West) HISR: Arizona						
New Mexico	−2.300 [0]	−0.570***(0.050)	1.049***(0.006)	−0.085 (0.058)[a]	0.938***(0.079)	0.000
Oklahoma	−2.843*[1]	−0.690***(0.048)	1.069***(0.006)	−0.148**(0.063)	0.994***(0.055)	0.006
Texas	−3.804***[0]	−0.512***(0.033)	1.059***(0.004)	−0.247**(0.124)	0.887***(0.063)	0.013

Notes: Figures in parentheses are standard errors, ***,**,* denote significance at the 1 %, 5 % and 10 % level, respectively. In the ADF test equation only the constant is included. The maximum lag length in the ADF test is determined using the Schwaz information criterion. The number of lag lengths is in brackets. The critical values used for the ADF test are those provided by MacKinnon (1996). [a] and [b] denote that the estimated standard errors are corrected using, respectively the heteroscedasticity consistent covariance matrix estimator, proposed by White (1980), and the heteroscedasticity autocorrelation consistent covariance matrix estimator, proposed by Newey and West (1987a, b)

The relevant results for every state in each BEA Region are set out on Table 10.2, together with the estimated coefficients from Eq. (10.6) and the coefficient of the error-correction term (θ_i). Table 10.2 reports also the short-run relation between a state's per-capita income and HISR (a_{i1}).[23]

Throughout the empirical application, it is important to keep in mind that the ECM framework implies a convergence pattern if $\beta_{i0} = 0$ and $\beta_{i1} = 1$. In the case which $\beta_{i0} \neq 0$ and/or $\beta_{i1} \neq 1$, then this is taken as indication of *permanent* regional inequalities. The latter seems to be the case for the US states, as shown in Table 10.2. Based on these results, however, a dissipating tendency is clearly suggested. How then this reconciles with the pattern of σ and β convergence established earlier? The conventional notion of convergence implies that regional inequalities in the long-run will disappear. On the other hand, the ECM framework implies an alternative aspect of convergence; dissipation of regional disparities as regions move towards the long-run steady-state equilibrium. Given the presence of 'Galton's fallacy' in the conventional measures of (σ and β) convergence the ECM provides a more robust approach.

In the subsequent analysis, therefore, the term 'convergence' will be used to indicate a tendency towards steady-state equilibrium coupled with dissipating disparities.

The regressions reveal an interesting pattern. According to the ADF tests, 11 states do not appear to cointegrate with their relevant HISR. Obviously, the property of convergence does not characterise these states (22 % of the total) and the ECM does not apply in such cases. Nevertheless, the results are reported for the sake of convenience. A striking fact from Table 10.2 is that in the Mideast, no state appears to converge with the HISR (District-of-Columbia). In the case of New York, the next state with the highest income in the Region, the ADF test is marginally statistically significant (at 10 % level), however, the error-correction term turns to be statistically insignificant. Bearing this in mind, it might be argued that District-of-Columbia is, in fact, an outlier and therefore not representative of the underlying tendencies. To verify this further, we conduct a similar analysis where each HISR is tested for convergence with the District-of-Columbia (Table 10.3).

The ADF tests do not confirm the hypothesis of cointegration in most cases.[24] Yet, the estimated error-correction terms appear to be statistically insignificant in all cases, enhancing therefore the argument that the District-of-Columbia is an outlier. In this case a choice for an alternative HISR in the region of Mideast must be made. Choosing the state with the second highest per-capita income (New York), produces the results in Table 10.4.

As perhaps anticipated the states in Mideast exhibit tendencies towards convergence with the state of New York. Accordingly, this state cannot be considered as an outlier and, consequently, is an appropriate proxy for steady-state equilibrium in

[23] We also conduct the usual Ramsey RESET test (Ramsey 1969) for specification errors. The obtained p-values indicate that, in general, there is no such problem.

[24] There are only two cases which yield marginally significant test values.

Table 10.3 District-of-Columbia – an outlier

HISR: District-of-Columbia						
	ADF test	β_{i0}	β_{i1}	θ_i	a_{i1}	Ramsey-RESET test (p-value)
California	−2.281	−0.0167	1.001***	−0.041	0.995***	0.304
	[1]	(0.113)	(0.13)	(0.052)[b]	(0.224)	
Illinois	−0.992	−0.468***	1.029***	−0.049	1.121***	0.002
	[0]	(0.128)	(0.015)	(0.055)[b]	(0.287)	
Connecticut	−2.754*	−0.541***	1.055***	−0.074	0.987***	0.034
	[1]	(0.093)	(0.011)	(0.052)[b]	(0.215)	
Missouri	−2.161	−1.102***	1.078***	−0.018	1.016***	0.028
		(0.143)	(0.016)	(0.046)[b]	(0.236)	
Wyoming	−1.357	−0.793***	1.052***	−0.048	1.068***	0.759
	[0]	(0.152)	(0.17)	(0.047)[b]	(0.190)	
Florida	−2.843*	−1.488***	1.121***	−0.017	1.017***	0.298
	[2]	(0.152)	(0.017)	(0.057)[b]	(0.230)	
Arizona	−2.174	−1.075***	1.070***	−0.047	1.121***	0.455
	[1]	(0.153)	(0.017)	(0.059)[b]	(0.269)	

Notes: Figures in parentheses are standard errors, ***, **, * denote significance at the 1 %, 5 % and 10 % level, respectively. In the ADF test equation only the constant is included. The maximum lag length in the ADF test is determined using the Schwarz information criterion. The number of lag lengths is in brackets. The critical values used for the ADF test are those provided by MacKinnon (1996). [a] and [b] denote that the estimated standard errors are corrected using, respectively the heteroscedasticity consistent covariance matrix estimator, proposed by White (1980), and the heteroscedasticity autocorrelation consistent covariance matrix estimator, proposed by Newey and West (1987a, b)

Table 10.4 New York as an alternative HISR for Mideast

	ADF test	β_{i0}	β_{i1}	θ_i	a_{i1}	Ramsey-RESET test (p-value)
Region 3 (Mideast) HISR: New York						
Delaware	−4.188***[1]	0.200***	0.974***	−0.275***	1.117***	0.146
		(0.048)	(0.005)	(0.075)	(0.077)	
Maryland	−4.683***[1]	−0.669***	1.067***	−0.173**	1.019***	0.025
		(0.044)	(0.005)	(0.069)[b]	(0.083)	
New Jersey	−3.913***[1]	−0.422***	1.049***	−0.206***	1.065***	0.002
		(0.032)	(0.004)	(0.064)[b]	(0.056)	
Pennsylvania	−2.587 [1]	−0.563***	1.044***	−0.177***	1.160***	0.757
		(0.041)	(0.005)	(0.059)[b]	(0.050)	

Notes: Figures in parentheses are standard errors, ***, **, * denote significance at the 1 %, 5 % and 10 % level, respectively. In the ADF test equation only the constant is included. The maximum lag length in the ADF test is determined using the Schwarz information criterion. The number of lag lengths is in brackets. The critical values used for the ADF test are those provided by MacKinnon (1996). [a] and [b] denote that the estimated standard errors are corrected using, respectively the heteroscedasticity consistent covariance matrix estimator, proposed by White (1980), and the heteroscedasticity autocorrelation consistent covariance matrix estimator, proposed by Newey and West (1987a, b)

Table 10.5 Convergence between HISRs

HISR: New York						
	ADF test	β_{i0}	β_{i1}	θ_i	a_{i1}	Ramsey-RESET test (p-value)
California	−2.764* [2]	0.038 (0.049)	0.993*** (0.006)	−0.156** (0.065)[b]	1.113*** (0.068)	0.020
Illinois	−1.476 [0]	−0.265*** (0.060)	1.022*** (0.007)	−0.103*** (0.038)	1.200*** (0.048)	0.061
Connecticut	−5.215*** [1]	−0.308*** (0.038)	1.044*** (0.004)	−0.251*** (0.079)[b]	1.119*** (0.055)	0.189
Missouri	−2.241 [0]	−0.893*** (0.071)	1.071*** (0.008)	−0.069** (0.032)	1.085*** (0.049)	0.760
Wyoming	−2.761* [1]	−0.582*** (0.100)	1.044*** (0.012)	−0.089* (0.053)[b]	1.107*** (0.101)	0.713
Florida	−2.892* [1]	−1.270*** (0.081)	1.114*** (0.009)	−0.108** (0.050)[a]	1.174*** (0.108)	0.000
Arizona	−2.140 [0]	−0.870*** (0.086)	1.064*** (0.010)	−0.140** (0.062)[b]	1.255*** (0.109)	0.414

Notes: Figures in parentheses are standard errors, ***, **, * denote significance at the 1 %, 5 % and 10 % level, respectively. In the ADF test equation only the constant is included. The maximum lag length in the ADF test is determined using the Schwarz information criterion. The number of lag lengths is in brackets. The critical values used for the ADF test are those provided by MacKinnon (1996). [a] and [b] denote that the estimated standard errors are corrected using, respectively the heteroscedasticity consistent covariance matrix estimator, proposed by White (1980), and the heteroscedasticity and autocorrelation consistent covariance matrix estimator, proposed by Newey and West (1987a, b)

the Region of Mideast. This is established further by testing for convergence between the state of New York and the remaining HISRs (Table 10.5); a process yielding better results compared to those using the state of District-of-Columbia.

Nevertheless, the property of convergence is not apparent amongst all HISRs. As the results indicate the cointegration ADF test is statistically significant at 10 % level for California, Wyoming and Florida while Connecticut yields the most robust results. It is worth noting that the aforementioned state exhibits the highest rate of adjustment amongst all the HISRs.

Insofar, the analysis appears as a classification of the US states into converging and non-converging states towards a HISR. The underlying structure of the ECM implies convergence towards different steady-state equilibria. The fact, however, that convergence is apparent amongst most HISRs suggests that the US states as a whole are in a process towards overall convergence.

Figure 10.3 shows the geographical location of converging and non-converging states identified using the ECM.[25] One conclusion is easily read out of Fig. 10.3. Most converging states share a common border with a HISR, suggesting the

[25] See Table A in the Appendix for the abbreviations used in Figs. 10.3 and 10.4.

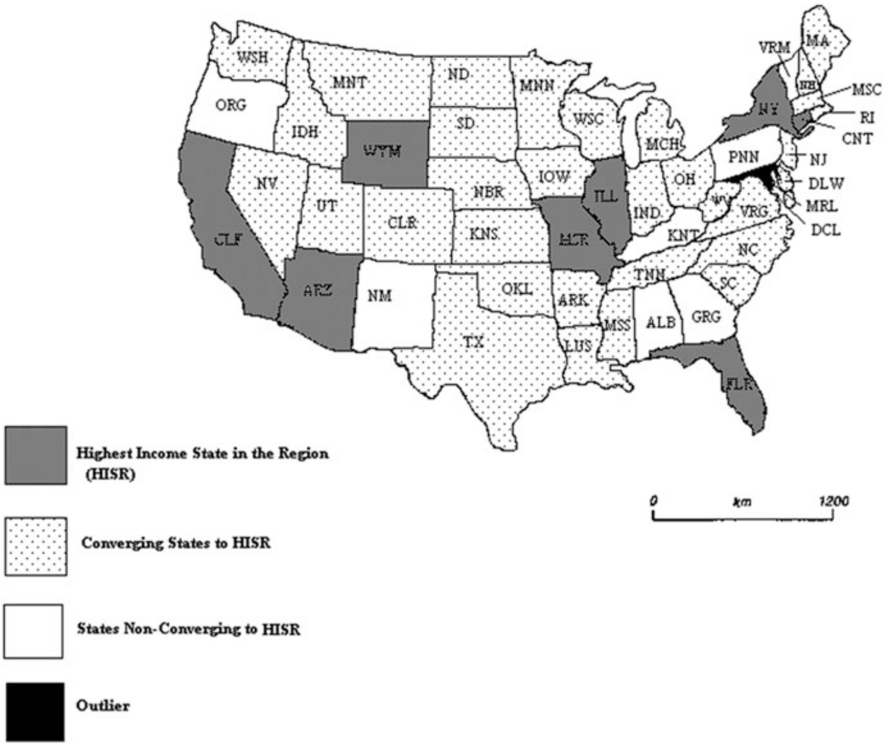

Fig. 10.3 Converging states, US, 1929–2005

existence of a strong geographical component in the process of long-run convergence. Striking exemptions of this pattern are the non-converging states of Vermont and Pennsylvania which fail to converge with their respective HISRs. It is beyond argument that neighbouring to a relatively prosperous state might cause beneficial effects. In the case of the two aforementioned states, such effects do not seem to have an impact on their convergence behaviour, irrespective of the physical proximity to a HISR, viz. New York. Absence of spillovers from geographical proximity to a HISR is also identified for the states of Alabama and Georgia; two non-converging states located close to Florida, the state with the highest per-capita income in the Region of South-East. Similarly, it should be visible in Fig. 10.3 that the convergence pattern of Oregon and New Mexico seems to be ‘indifferent’ to the proximity to California and Arizona, respectively. In the case of Kentucky, finally, proximity to two HISRs (Illinois and Missouri) is a factor unrelated to the convergence behaviour of this state.

A common factor in most cases is that the HISRs in question contain big agglomerations (e.g. New York City, Los Angeles, etc). It is almost an article of faith in regional economics that agglomerations cause negative, as well as, positive effects in the area where located. However, the exceptional cases discussed here,

Table 10.6 Adjustment process

State	Speed of adjustment	Years to adjust(n)
Idaho	0.580	5
Iowa	0.553	5
Nevada	0.532	6
Nebraska	0.467	6
Michigan	0.463	6
Montana	0.411	7
Ohio	0.395	8
Minnesota	0.388	8
South Dakota	0.379	8
Wisconsin	0.343	9
North Dakota	0.316	9
Mississippi	0.293	10
West Virginia	0.283	11
Colorado	0.282	11
Delaware	0.275	11
Indiana	0.275	11
Kansas	0.257	12
Virginia	0.252	12
Texas	0.247	12
Utah	0.245	12
Maine	0.235	13
Massachusetts	0.234	13
Tennessee	0.226	13
New Jersey	0.206	15
Arkansas	0.206	15
North Carolina	0.179	17
Maryland	0.173	17
Louisiana	0.173	17
New Hampshire	0.169	18
South Carolina	0.153	20
Oklahoma	0.148	20
Washington	0.147	20

imply that close proximity to a state containing an agglomerative centre might cause adverse effects to the convergence paths of the surrounding states.

Nevertheless, that there will be exceptions does not invalidate the ECM approach, or make it inapplicable. As can be seen from Fig. 10.3, an ECM is able to describe adequately the convergence path for the vast majority of the US states.

A further advantage of the ECM is that it allows for a distinction of the converging states based on the rate at which cover the distance between long-run equilibrium. For each converging state the calculation of the years (n) to adjust is made for the 95 % of the disequilibrium, and performed according to the following formula (Romer 1996):

$$n = -\frac{\ln(0.05)}{|\theta_i|} \tag{10.7}$$

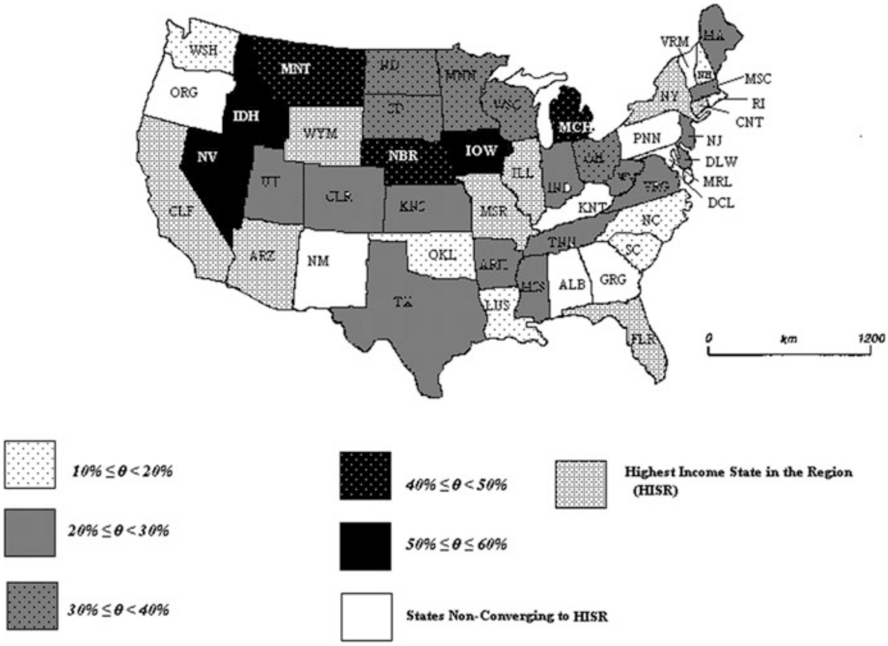

Fig. 10.4 Adjustment rates

Table 10.6 shows the adjustment parameters together with the years required for deviations from steady-state equilibrium to almost dissipate.

A variation in the adjustment rate is somehow anticipated, given the structure of the ECM. Based on the estimated rates, it might be argued that a relatively slow adjustment process is followed by the majority of the converging states. In particular, 43 % of the US states converge towards their steady-state equilibria at a rate in the range between 10 % and 30 %. Fewer states (12 %) exhibit faster rates of adjustment (in the range between 40 % and 60 %). The geographical distribution of the converging states according to their speed of adjustment is illustrated by Fig. 10.4.

It goes without saying that a more complicated picture is expected since a new dimension is added. States are now ordered by their adjustment rates, which show a high degree of diversity causing difficulties in detecting an underlying pattern. Suffice to state that a kind of 'clustering' is evident for four states located in the north part of the country (North Dakota, South Dakota, Minnesota and Wisconsin). Such results imply that the impact of spatial dependence does contribute to the observed patter of convergence. The empirics in this paper, however, to some extent ignore this spatial dimension, apart from the recognition of a 'leading' spatial unit (HISR). While there is an innovative literature on spatial econometrics in analysing regional convergence (e.g. Ezcurra et al. 2007; Fingleton 2001; Gibbons and Overman 2010; Fingleton and Fischer 2010; Acosta 2010; Rey and Montouri

1999; Rey and Janikas 2005; Rey and Dev 2006), this is concentrated almost exclusively using cross-section data. Incorporating, however, spatial factors in an error-correction model, which is adopted presently, goes beyond the scope of this chapter.

10.4 Conclusion

For more than 30 years the question of income convergence has become one of the foremost topics in economic research. Different empirical studies using various econometric techniques in diverse contexts were conducted. For the US states, especially, the issue of income convergence has generated, and continues to do so, a vast literature. Our chapter, however, does not simply add to the list of successful tests of income convergence across the US states. Most importantly, our study provides new evidence of income convergence using an ECM, extending its applicability beyond examining trends in employment or unemployment.

One conclusion to emerge from this study is that it makes little sense to concentrate upon the simple question as to whether or not convergence exists. Following the econometric estimations, the hypothesis that the US states move towards different steady-state equilibria appears to be confirmed. This outcome is in accordance with a fast growing literature on club convergence (e.g. Galor 1996; Galor and Tsiddon 1991; Corrado et al. 2005; Fischer and Stirböck 2006; Alexiadis 2010a, b). The importance of the ECM for an understanding of the pace and rhythm of regional convergence can now be appreciated. Once we recognize the dynamic nature of convergence, the high catch-up rates implied by cross-section tests seem less startling, and we get a different impression of the steady-state equilibrium. Using an ECM, this notion, is expressed in a more elaborated way compared to a simple measure of average per-capita income. To be more concrete, the state with the highest per-capita income in a region is applied in an attempt to depict the long-run equilibrium. Such a proxy also allows for the effects stemming from geographical proximity to be taken into account in a time-series framework, leading to one of the major findings in this chapter.

The results reported in this chapter cast a sceptical view on the positive effects of agglomerations in promoting income convergence in surrounding states. Instead, they lend support to a perspective that emphasises the argument that in an intraregional system, the benefits of one region are frequently the costs of another, i.e. a process of interaction. This point is aptly summarised by Gruber and Soci (2010), when they suggest that: ‘Although they can be virtually distinct, cities, towns, villages and open countryside are all part of the same functional economic and social system. A village household may rely on neighbouring towns or larger urban centres for jobs, shopping, schools, health care and leisure. Urban households may use the countryside for travel, sport and recreation and may depend on it for the provision of food, water and energy’.

Hence, it might be argued that the effects of agglomerations on regional convergence can be examined in a more effective manner within the ambit of an ECM, providing thus a ‘nexus’ between time-series and spatial analysis. The empirical applications of regional convergence models, however, raise as many questions as they answer. The evidence that is put forward should however be seen as indicative at best and the analysis should be replicated as additional data become available to check whether our conclusions can be confirmed. However, the framework introduced in this chapter is versatile enough to incorporate alternative notions and extensions. But that task still remains to be carried out. What is then the purpose of such a chapter? Perhaps our main intention is to provoke further interest in the applicability of models based on the structure of error-correction mechanisms in examining the morphology of income convergence across regions.

Appendix

The States used in the empirical analysis
Alabama (ALB)
Arizona (ARZ)
Arkansas (ARK)
California (CLF)
Colorado (CLR)
Connecticut (CNT)
Delaware (DLW)
District-of-Columbia (DCL)
Florida (FLR)
Georgia (GRG)
Idaho (IDH)
Illinois (ILL)
Indiana (IND)
Iowa (IOW)
Kansas (KNS)
Kentucky (KNT)
Louisiana (LUS)
Maine (MA)
Maryland (MRL)
Massachusetts (MSC)
Michigan (MCH)
Minnesota (MNN)
Mississippi (MSS)
Missouri (MSR)
Montana (MNT)
Nebraska (NBR)
Nevada (NV)
New Hampshire (NH)

(continued)

The States used in the empirical analysis
New Jersey (NJ)
New Mexico (NM)
New York (NY)
North Carolina (NC)
North Dakota (ND)
Ohio (OH)
Oklahoma (OKL)
Oregon (ORG)
Pennsylvania (PNN)
Rhode Island (RI)
South Carolina (SC)
South Dakota (SD)
Tennessee (TNN)
Texas (TX)
Utah (UT)
Vermont (VRM)
Virginia (VRG)
Washington (WSH)
West Virginia (WV)
Wisconsin (WSC)
Wyoming (WYM)

References

Acosta P (2010) The "flypaper effect" in presence of spatial interdependence: evidence from Argentinean municipalities. Ann Reg Sci 44(3):453–466

Aghion P, Howitt P (1998) Endogenous growth theory. MIT Press, Cambridge, MA

Alexiadis S (2010a) Regional convergence-clubs and dynamic externalities. Ital J Reg Sci 9(1): 41–64

Alexiadis S (2010b) Interregional differences in adoptive abilities: an alternative framework. Reg Sci Inq 1(2):41–52

Alexiadis S, Eleftheriou K (2010) A note on the morphology of regional unemployment in Greece. Econ Bull 30(4):2779–2786

Alexiadis S, Tomkins J (2004) Convergence-clubs in the regions of Greece. Appl Econ Lett 11(6): 387–391

Alexiadis S, Tsagdis D (2010) Is cumulative growth in manufacturing productivity slowing down in the EU12 regions? Cambridge J Econ 34(6):1001–1017

Angulo A, Gil J, Gracia A (2001) Calorie intake and income elasticities in EU countries: a convergence analysis using cointegration. Pap Reg Sci 80(2):165–187

Baddeley M, Martin R, Tayler P (1998) European regional unemployment disparities: convergence or persistence? Eur Urban Reg Stud 5(3):195–215

Baddeley M, Martin R, Tayler P (2000) Regional wage rigidity: the European Union and United States compared. J Reg Sci 40(1):115–142

Badinger H, Müller W, Tondl G (2004) Regional convergence in the European Union, 1985–1999: a spatial dynamic panel analysis. Reg Stud 38(3):241–253

Baldwin R, Forslid R, Martin P, Ottaviano G, Robert-Nicoud F (2003) Economic geography and public policy. Princeton University Press, Princeton

Barro R, Sala-i-Martin X (1991) Convergence across states and regions. Brooking Pap Econ Act 1:107–182

Barro R, Sala-i-Martin X (1992a) Convergence. J Polit Econ 100(2):223–251

Barro R, Sala-i-Martin X (1992b) Regional growth and migration: a Japanese-US comparison. J Jpn Int Econ 6(4):312–346

Baumol W (1986) Productivity growth, convergence and welfare: what the long-run data show. Am Econ Rev 76(5):1072–1085

Bernard A, Durlauf S (1995) Convergence of international output. J Appl Econometr 10(2): 97–108

Bernard A, Jones C (1996) Productivity and convergence across US States and industries. Empirical Econ 21(1):113–135

Bliss C (1999) Galton's fallacy and economic convergence. Oxford Econ Pap 51(1):4–14

Borts G, Stein J (1964) Economic growth in a free market. Columbia University Press, New York

Boyle G, McCarthy T (1999) Simple measures of convergence in per capita GDP: a note on some further international evidence. Appl Econ Lett 6(6):343–347

Button K, Pentecost E (1995) Testing for convergence of the EU regional economies. Econ Inq 33(4):664–671

Cannon E, Duck N (2000) Galton's fallacy and economic convergence. Oxford Econ Pap 52(2):415–419

Capello R (2006) Reg Econ. Routledge, London

Carlino G, Mills L (1993) Are U.S. regional incomes converging? A time-series analysis. J Monetary Econ 32(2):335–346

Checherita C (2009) Variations on economic convergence: the case of the United States. Pap Reg Sci 88(2):259–278

Cheshire P, Carbonaro G (1995) Convergence – divergence in regional growth rates: an empty black box? In: Armstrong H, Vickerman R (eds) Convergence and divergence among european regions. Pion, London, pp 89–111

Christopoulos D, Tsionas E (2007) Are regional incomes in the USA converging? A non-linear perspective. Reg Stud 41(4):525–530

Corrado L, Martin R, Weeks M (2005) Identifying and interpreting regional convergence clusters across Europe. Econ J 115(502):C133–C160

Cuadrado-Roura J (1996) Regional disparities and territorial cohesion in the EC. In: Cuadrado-Roura J, Nijkamp P, Salvá P (eds) Moving frontiers: economic restructuring, regional development and emerging networks. Avebury, Aldershot, pp 3–22

Cuadrado-Roura JB, García-Greciano B, Raymond J (1999) Regional convergence in productivity and productive structure: the Spanish case. Int Reg Sci Rev 22(1):35–53

Dalgaard C, Vastrup J (2001) On the measurement of σ-convergence. Econ Lett 70(2):283–287

De la Fuente A (2002) On the sources of convergence: a closer look at the Spanish regions. Eur Econ Rev 46(3):569–599

Di Liberto A, Pigliaru F, Mura R (2008) How to measure the unobservable: a panel technique for the analysis of TFP convergence. Oxford Econ Pap 60(2):343–368

Dickey D, Fuller W (1981) Likelihood ratio statistics for autoregressive time-series with a unit-root. Econometrica 49(4):1057–1072

Dunford M (1993) Regional disparities in the european community: evidence from the REGIO databank. Reg Stud 27(8):727–743

Elster J (1989) Nuts and bolts for the social sciences. Cambridge University Press, Cambridge

Engle R, Granger C (1987) Cointegration and error–correction: representation, estimation and testing. Econometrica 55(2):251–276

Esposti R, Bussoletti S (2008) Impact of objective-1 funds on regional growth convergence in the European Union: a panel-data approach. Reg Stud 42(2):159–173

Ezcurra R, Pascual P, Rapún M (2007) Spatial inequality in productivity in the European Union: sectoral and regional factors. Int Reg Sci Rev 30(4):384–407

Fingleton B (1997) Specification and testing of Markov chain models: an application to convergence in the European Union. Oxford Bull Econ Stat 59(3):385–403
Fingleton B (2001) Theoretical economic geography and spatial econometrics: dynamic perspectives. J Econ Geogr 1(2):201–225
Fingleton B, Fischer M (2010) Neoclassical theory versus new economic geography: competing explanations of cross-regional variation in economic development. Ann Reg Sci 44(3): 467–491
Fischer M, Stirböck C (2006) Pan-European regional income growth and club convergence. Ann Reg Sci 40(4):693–721
Galor O (1996) Convergence? Inferences form theoretical models. Econ J 106(437):1056–1069
Galor O, Tsiddon D (1991) Technological breakthroughs and development traps. Econ Lett 37(1): 11–17
Gibbons S, Overman H (2010) Mostly pointless spatial econometrics, SERC discussion paper no. 61, Oct
Gray D (2004) Persistent regional unemployment differentials revisited. Reg Stud 38(2):167–176
Gray D (2005) An examination of regional interaction and super-regions in Britain: an error-correction model approach. Reg Stud 39(5):619–632
Gruber S, Soci A (2010) Agglomeration, agriculture and the perspective of the periphery. Spat Econ Anal 5(1):43–72
Hierro M, Maza A (2010) Per-capita income convergence and internal migration in Spain: are foreign-born migrants playing an important role? Pap Reg Sci 89(1):89–107
Hunt G (2006) Population-employment models: stationarity, co-integration, and dynamic adjustment. J Reg Sci 46(2):205–244
Hurst C, Thisse J, Vanhoudt P (2000) What diagnosis for Europe's ailing regions? Eur Invest Bank Pap 5(1):9–29
Ioannides Y, Overman H (2004) The spatial evolution of the U.S. urban system. J Econ Geogr 4(2):131–156
Islam N (2003) What have we learnt from the convergence debate? J Econ Surv 17(3):309–362
Keil S (1997) Regional trends in British manufacturing employment: tests for stationarity and co-integration, 1952–1989. Reg Stud 31(1):13–24
Le Gallo J (2004) Space-time analysis of GDP disparities among European regions: a Markov chains approach. Int Reg Sci Rev 27(2):138–163
Li H, Haynes K (2010) Economic structure and regional disparity in China: beyond the Kuznets transition. Int Reg Sci Rev 34(2):157–190
Lichtenberg F (1994) Testing the convergence hypothesis. Rev Econ Stat 76(3):576–579
Lopez-Bazo E, Vaya E, Artis M (2004) Regional externalities and growth: evidence from European regions. J Reg Sci 44(1):43–73
MacKinnon J (1996) Numerical distribution functions for unit-root and cointegration tests. J Appl Econometr 11(6):601–618
Mankiw N, Romer D, Weil N (1992) A contribution to the empirics of economic growth. Q J Econ 107(2):407–438
Martin R (1997) Regional unemployment disparities and their dynamics. Reg Stud 31(3):237–252
Martin P (1998) Can regional policies affect growth and geography in Europe? World Econ 21(8): 757–774
Martin R (1999) The new geographical turn in economics: some critical reflections. Cambridge J Econ 23(1):65–91
Martin R, Tyler P (2000) Regional employment evolutions in the European Union: a preliminary analysis. Reg Stud 34(7):601–616
McGuinness S, Sheehan M (1998) Regional convergence in the UK, 1970–1995. Appl Econ Lett 5(10):653–658
Neven D, Gouyette C (1995) Regional convergence in the European Community. J Common Mark Stud 33(1):47–65
Newey W, West K (1987a) Hypothesis testing with efficient method of moments estimation. Int Econ Rev 28(3):777–787

Newey W, West K (1987b) A simple positive semi-definite, heteroscedasticity and autocorrelation consistent covariance matrix. Econometrica 55(3):703–708
Overman H, Puga D (2002) Unemployment clusters across European countries and regions. Econ Policy 17(34):117–147
Paci R, Pigliaru F (1997) Structural change and convergence: an Italian regional perspective. Struct Change Econ Dyn 8(3):297–318
Phillips P, Perron P (1988) Testing for a unit-root in time-series regression. Biometrika 75(2): 335–346
Quah D (1996) Regional convergence clusters in Europe. Eur Econ Rev 40(6):951–958
Ramsey J (1969) Tests for specification errors in classical linear least squares regression analysis. J R Stat Soc Series B 31(2):350–371
Rey S, Dev B (2006) σ-convergence in the presence of spatial effects. Pap Reg Sci 85(2):217–234
Rey S, Janikas M (2005) Regional convergence, inequality and space. J Econ Geogr 5(2):155–176
Rey S, Montouri B (1999) US regional income convergence: a spatial econometric perspective. Reg Stud 33(2):143–156
Rodríguez-López J, Martínez D, Romero-Ávila D (2009) Persistence of inequalities across the Spanish regions. Pap Reg Sci 88(4):841–862
Rodríguez-Pose A (1999) Convergence or divergence? Types of regional responses to socio-economic change in Western Europe. Tijdschrift voor Economische en Sociale Geographie 90(4):363–378
Rodríguez-Pose A (2001) Is R&D investment in lagging areas of Europe worthwhile? Theory and empirical evidence. Pap Reg Sci 80(3):275–295
Rodríguez-Pose A, Fratesi U (2004) Between development and social policies: the impact of European structural funds in objective-1 regions. Reg Stud 38(1):97–113
Rogers M (2003) A survey of economic growth. Econ Rec 79(244):112–135
Romer D (1996) Advanced macroeconomics. McGraw-Hill, New York
Sala-i-Martin X (1996) The classical approach to convergence analysis. Econ J 106(437): 1019–1036
Solow R (1956) A contribution to the theory of economic growth. Q J Econ 70(1):65–94
Solow R (1957) Technical change and the aggregate production function. Rev Econ Stat 39(3): 312–320
Sun L, Hong E, Li T (2010) Incorporating technology diffusion, factor mobility and structural change into cross-region growth regression: an application to China. J Reg Sci 50(3):734–755
Tsionas E (2000) Regional growth and convergence: evidence from the United States. Reg Stud 34(3):231–238
Tsionas E (2001) Regional convergence and common, stochastic long-run trends: a re-examination of the US regional data. Reg Stud 35(8):689–696
White H (1980) A heteroscedasticity-consistent covariance matrix and a direct test for heteroscedasticity. Econometrica 48(4):817–838
Williamson J (1965) Regional inequalities and the process of national development. Econ Dev Cult Change 13(4):3–45

Chapter 11
Returns to Communication in Specialised and Diversified US Cities

Suzanne Kok

11.1 Introduction

A key factor in today's urban wealth is the means by which cities reduce costs of communication. Rapid progress in transport, information and communication technologies lowered the costs of production at distance. Still, in 2009 metropolitan areas were responsible for 85 % of US employment, income and production. The significance of personal communication for innovation is a fundamental aspect of the current economic success of cities. The economic structure of cities varies; diversified cities focusing on producing ideas and specialised cities focusing on producing products successfully coexist in the US. Is communication equally important and valued within both city types?

Variation in the advantages of clustering of economic activity resulted in the existence of different economic city structures. Typically two types of cities coexist in the US: cities with a specialised industrial structure and cities with a diversified industrial structure (Duranton and Puga 2000). Within specialised cities firms benefit from cost sharing, labour matching and learning from similar firms. The production costs are relatively low in these cities and the focus lies on producing products. A diversified environment with a wide variety of firms and ideas is more beneficial for innovation and producing ideas. The knowledge spillovers are more extensive in diversified cities but the production costs are higher. Especially for young firms and products the flows of ideas within diversified cities are key to success, while more mature firms flourish in specialised cities (Duranton and Puga 2001; Desmet and Rossi-Hansberg 2009). These variations in trade-offs between knowledge spillovers and production costs suggest that communication is less important within specialised cities. However, this suggestion does not reconcile with the assigned role of knowledge spillovers in the success of specialised clusters such as Silicon Valley.

S. Kok (✉)
University of Groningen and CPB Netherlands Bureau for Economic Policy Analysis,
Van Stolkweg 14, 2585JR Den Haag, The Netherlands
e-mail: s.j.kok@cpb.nl

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In this paper we focus on the role of communication within the coexistence of diversified and specialised cities. We measure the individual returns to communication job tasks in a cross-section of both city types in the US. Workers, who communicate more in and outside the organisation, earn higher wages. The main contribution to regional science and policy is our finding that the importance of communication decreases with the specialisation level of cities.

First, a simple framework is set out to guide our empirical analyses. The framework captures an economy with perfect competition, free firm entry, full mobility of labour and spatial wage differences. The differences in wages across local labour markets are compensated with differences in productivity, labour ability and other local characteristics. In equilibrium both firms and workers are indifferent towards location. The productivity of a firm increases with the specialisation level of the city when the firm operates in the dominant industry of the city, hence the industry in which the city specialises. The productivity benefits of local communication decrease with the specialisation level of the city.

Second, we estimate the returns to communication job tasks for workers in the largest 168 US cities in 2009. Individual data from the Current Population Survey is combined with the job characteristics from the ONET Skill Survey. The performance of communication job tasks is defined by the work context and work activities information from the ONET Skill Survey. We start by estimating simple wage regressions in which we test the correlation between communication job tasks and individual wage, conditional on several individual and city characteristics. We find a positive relation between the number of communication job tasks a worker performs and his wage. Furthermore, our estimates show that this relation is present in both specialised and diversified cities but diminishes with the specialisation level of the city. The correlation between wage and communication is significantly stronger in diversified cities than in specialised cities.

Third, we control for differences in unobserved ability and perform IV-estimates. The occupational communication job tasks are instrumented with a language-skill proxy. Workers with weaker language-skills are assumed to be less likely to perform communication job tasks. The language-skill proxy measures the share of workers in an occupation who did not grow up in an English-speaking household. Several tests prove that the language-skill proxy does not measure the wage impact of cultural differences. Following Ciccone and Hall (1996) historical population (1930) is used as an instrument for current city size or the extent to which the industrial structure is either specialised or diversified. The IV-estimates correspond to the OLS-estimates. A one standard deviation increase in the importance of communication, increases wages by 18 % of a standard deviation. However, in cities with a *specialised sectoral structure*, these returns are about 16 % of a standard deviation. The returns are somewhat higher in *large* cities: about 21 % of a standard deviation. The returns to communication do not vary with the diversity level of the city. The variation in returns to communication over city types explains part of the lower wages in specialised cities and part of the higher wages in larger cities.

Lastly, we carry out several robustness checks and analyse alternative specifications. First, we test the sensitivity of the measure of communication and measure the returns to the relative importance of communication, non-routine interactive tasks as in Autor et al. (2003) and people skills as in Bacolod et al. (2009). Next, we perform an additional test on the effect of unobserved ability and allow the returns to communication to vary across skill level (Glaeser and Mare 2001). The results are robust to all these specifications. Moreover, the results hold for both industrial sectors and service sectors.

Our work is based on a small theoretical literature explaining the coexistence of diversified and specialised cities. Duranton and Puga (2001) and Desmet and Rossi-Hansberg (2009) set up a dynamic general-equilibrium model which explain the co-existence of the two city types within the life-cycle of respectively firms and industries. Glaeser and Ponzetto (2007), Gaspar and Glaeser (1998) and Ioannides et al. (2008) model two rival spatial effects of technological progress. All these papers underline their theory with empirical analyses. Furthermore, Harrison et al. (1996), Kelley and Helper (1999) and Feldman and Audretsch (1999) document the contributions of sectoral diversity towards new production processes and new products.

A very broad and extensive literature indicates the (non random) coexistence of diversified and specialised cities (e.g. Duranton and Puga 2000; Ellison and Glaeser 1999) and the relative advantages at the city level (see Glaeser and Gottlieb 2009 for an overview). The importance of communication in the current wealth of cities relates to empirical contributions of (among others) Jaffe et al. (1993), Rauch (1993), Charlot and Duranton (2004), Bacolod et al. (2009) and Florida et al. (2012). Our work adds to these contributions by focussing on the variation in returns to communication between different city types. Therefore, we focus on the suggested micro-foundations of the coexistence of these two city types as in Duranton and Puga (2001).

The rest of the paper is structured as follows. The next section discusses a simple framework underlying our ideas and Sect. 11.3 sets out the estimation strategy of this framework. Section 11.4 describes the construction of the database and some descriptive statistics. Section 11.5 presents the OLS-estimates and Sect. 11.6 the IV-estimates. In Sect. 11.7 several other specifications are tested for robustness. Section 11.8 concludes.

11.2 Spatial Wage Differences and Communication

Before we present the estimates of the returns to communication we set out a framework which captures the underlying mechanism. Our framework explains the existence of spatial wage differences and the role of communication. It relies on the assumption that in equilibrium wage differences are possible while workers and firms should be indifferent to location. Local markets i are characterised by (both observed and unobserved) ability, productivity level, price level, and industrial structure (specialisation level).

11.2.1 General Setting

We consider an economy with perfect competition, free firm entry and full mobility of labour. Firms either focus on mass-products or on new and developing products. Firm's output is a function of productivity (A), number of workers (L) and city characteristics (C): $Y = f(A,L,C)$. These factors are mutually dependent. The productivity of a firm, for example, depends on its workers and its location and varies between mass-production and developing production (see Duranton and Puga 2001; Desmet and Rossi-Hansberg 2009). The free entry assumption implies that firms obtain zero profits. As often noted in the literature, large spatial wage differences exist (e.g. Glaeser and Mare 2001). The spatial wage differences are compensated by spatial variation in the input factors productivity, labour and city characteristics. In equilibrium workers and firms are indifferent regarding location i. The spatial variation in A and C explains why not all workers move to the high wage cities and not all firms move away from these cities.

11.2.2 Spatial Distribution of Firms

Following the theoretical work of Duranton and Puga, firms locate in a less specialised (or diversified) city during the learning stage and development of their ideal production process. In these 'nursery' cities firms learn from the ideas and knowledge of a broad variety of firms. Human capital externalities are crucial for the productivity and innovation of new products as the cross-fertilisation of ideas and knowledge stimulates the generation of new ideas (Lucas 1988; Duranton and Puga 2001; Desmet and Rossi-Hansberg 2009). When firms find their optimal production process and move to mass-production they relocate to more specialised cities. Specialised cities house a co-agglomeration of similar firms which enables firms to share, match and learn from their direct competitors.

11.2.3 Productivity

The ability of the local work force varies over space (Combes et al. 2008). All firms benefit from a productive labour force (φ_i). The determinants of local productivity vary with the local specialisation level (ρ_i). Firms who focus on mass-production and locate in specialised cities benefit from sharing facilities, matching labour and knowledge spillovers from similar firms. If the firm operates in the dominant local industry, productivity rises with the specialisation level (M^{ρ_i}).[1] A mature firm in the textile industry benefits from the co-location of textile industry and a high local specialisation level in this industry.

[1] M is the productivity effect of operating in the local dominant industry. This effect increases with the specialisation level of the city.

As indicated, both firms in specialised and diversified cities benefit from learning and communication with other firms. The cross-fertilisation of ideas is more likely to happen when people meet face to face. Not only is face to face contact a very efficient communication technology, it also helps solving incentive problems and more importantly facilitates learning and human capital externalities (Storper and Venables (2004)).[2] The amount of local knowledge spillovers and communication depends on the allocation of labour between core work activities and communication tasks. Core work activities are the job tasks of the occupation of the worker. Communication tasks contain the communication with other workers (in or outside the firm) about work activities. θ is the fraction of labour spend on communication tasks. The firm allocates labour optimally between work activities and communication tasks given local characteristics. However, learning and communication are more crucial for firms in less specialised cities which still optimize their production process by learning from others (Duranton and Puga 2001; Desmet and Rossi-Hansberg 2009).

To sum up, the productivity of a firm (A) depends on whether the firm operates in the local dominant industry (M), the specialisation level of the local industry (ρ_i), the amount of local communication (θL) and the ability or productivity of the local work force (φ_i). Firms which operate in the local industry experience a productivity which increases with the local specialisation level. The productivity benefits of local communication, on the other hand, decrease with the specialisation level of the city.

$$A = M^{\rho_i} E^{(1-\rho_i)} \varphi_i \tag{11.1}$$

where $0 < \rho_i < 1$ and $E = d\theta L$

Labour input to produce output only includes the fraction of labour spend on work activities ($(1-\theta)L$). Output is produced with labour spend on work activities (which decreases with the fraction spend on communication) at a productivity level that increases with the fraction spend on communication:

$$Y = A((1-\theta)L) \tag{11.2}$$

11.2.4 Optimal Allocation of Labour

Output is only produced with work activities while wages and rents are paid for both communication tasks and work activities (L). Local wages (W_i) and rents (R_i) are given. Congestion costs cause the local rents to rise with the size of the local market.

$$\pi = A(1-\theta)L - W_i L - R_i \tag{11.3}$$

[2] This explains why human capital spillovers and learning are bound by distance (Jaffe et al. 1993; Jacobs 1969).

There is a trade-off between spending labour on communication and increasing productivity and spending labour on work activities and increasing production input. This trade-off varies with the local level of specialisation (ρ_i). Firms maximize profits (π), given the local dominant industry, specialisation level and rents, and optimally allocate labour between communication tasks and work activities. They optimize the following equation:

$$\pi = M^{\rho_i}(d\theta L)^{(1-\rho_i)}\varphi_i(1-\theta)L - W_iL - R_i \tag{11.4}$$

Optimizing Eq. (11.4) leads to the following optimal allocation of labour between core activities ($1-\theta$) and communication about core activities (θ), given the local specialisation level ρ_i:

$$(1-\theta) = \frac{\theta}{1-\rho_i} \tag{11.5}$$

Substituting the optimal allocation of labour into Eq. (11.3) it follows that:

$$\pi = b\varphi_i M^{\rho_i}(\theta L)^{(2-\rho_i)} - W_iL - R_i \tag{11.6}$$

where $b = \dfrac{d^{1-\rho_i}}{1-\rho_i}$

11.2.5 Individual Wages

Firm entry is free which implies zero profits. This leads to the following total labour costs:

$$W_iL = b\varphi_i M^{\rho_i}(\theta L)^{(2-\rho_i)} - R_i \tag{11.7}$$

We assume that individual wages correspond to individual ability. Setting L to 1, individual worker wage is then:

$$W_k = b\varphi_k M^{\rho_i}(\theta_k)^{(2-\rho_i)} - R_i \tag{11.8}$$

The individual wage is determined by a constant, the ability of the worker (φ_k), the level of local specialisation (ρ_i), whether the worker works in the dominant industry (M), the fraction of labour which the worker spends on communication (θ_k), and the average local rent costs (R_i). If the worker works in the dominant local industry, his wage rises with the local industrial specialisation of the relevant industry. However, the wage benefits of communication decrease with the local level of specialisation:

$$\frac{\partial W_k}{\partial \theta_k} > 0 \tag{11.9}$$

$$\frac{\partial W_k^2}{\partial \theta_k \rho_k} < 0 \tag{11.10}$$

11.3 Empirical Strategy

11.3.1 Reduced Form

We bring Eq. (11.8) to the data and estimate the reduced form for worker k in city i.

$$\begin{aligned} \ln w_{ki} = {} & \alpha_1 + \alpha_2 \hat{\varphi}_k + \alpha_3 \hat{M}_k + \beta_1 \hat{\theta}_k + \beta_2 \hat{\rho}_i + \beta_3 \hat{R}_i + \gamma_1 (\hat{\theta}_k \cdot \hat{\rho}_i) \\ & + \gamma_2 (\hat{M}_k \cdot \hat{\rho}_i) + \varepsilon_{ki} \end{aligned} \tag{11.11}$$

where w_{ki} is the hourly wage earnings of individual k, in city (Metropolitan Statistical Area) i. Individual ability is estimated by $\hat{\varphi}_k$: a set of standard, demographical controls (age, age squared, gender, race and marital status), a set of occupational dummies and a set of education dummies of the highest grade completed. $\hat{M}_k$ represents the productivity effect of mass-production and indicates whether individual k works in the dominant industry city i or not. Indicator $\hat{\theta}_k$ denotes the estimate of the performance of communication tasks by worker k.[3] The local level of specialisation is estimated with the Regional Specialisation Index (*RSI*). The *RSI* calculates the maximum over-representation (subject to national share) of an industry in the city. $\hat{\rho}_i = max_i \ logE_{ij} - \log E_j$ in which E_{ij} represents the employment share of industry j in city i and E_j the employment share of industry j in national employment. We allow the returns to communication to vary with the local specialisation level $\left(\gamma_1(\hat{\theta}_k \cdot \hat{\rho}_i)\right)$. The returns to working in the local dominant industry vary with the local level of specialisation as well $\left(\gamma_2(\hat{M}_k \cdot \hat{\rho}_i)\right)$. Lastly, $\hat{R}_i$ indicates the average rent costs in city i.

[3] As explained in the next section, data limit us to measure communication at the occupational level.

11.3.2 Measurement

The estimation of this empirical model requires a number of assumptions. First, the indicator for communication tasks $(\hat{\theta}_k)$ and its interaction with local industrial specialisation $(\hat{\theta}_k \cdot \hat{\rho}_i)$ are measured at aggregated levels and do not vary by worker. The dependent variable (w_{ki}) is however measured at the worker level. This leads to underestimation of the standard errors as indicated by Moulton (1990). To avoid this issue, we cluster standard errors at the occupational level.

Second, endogeneity issues may bias our OLS-estimates. The ability of individuals is estimated and not fully observed. The measurement error ε_{ki} includes ability characteristics (A_k) such as talent and work discipline and some measurement error at the individual and city level (μ_{ki}): $\varepsilon_{ki} = A_k + \mu_{ki}$. When A_k correlates with the local specialisation level ρ_i or city size R_i, we cannot isolate the effect of these indicators on wages and the estimates become biased. To deal with endogeneity, Sect. 11.6 shows the results of instrumenting communication.

Third, specialisation and diversity are not opposite measures. The *RSI* measures the over-representation of an industry in city *i* while the local diversity level reflects the mixture of industries within the city. Thus, the regional diversity index (*RDI*) captures all industries in the city while *RSI* only includes information on the dominant industry.[4] We experiment with including both *RSI* and *RDI*.

Fourth, specialised cities tend to be smaller than diversified cities (e.g. Duranton and Puga 2000).[5] Hence, $\hat{\rho}_i$ correlates strongly with city size. The correlation between the size and the specialisation (and diversity) is too strong to include both in the regressions. Therefore, we attempt additional estimates with only city size and a cross-term of city size with communication.

Lastly, work activities might also involve communication. Especially low skilled service occupations often involve several communication tasks such as waiting tables. We aim however to measure the returns to communication *about* job activities, for example a worker who informs his manager about the results of his analyses. To distinguish between these two forms of communication we include information about communication work activities as well. Communication work activities are defined as the ONET work activity ‘performing for or working directly with the public’ with the description: ‘Performing for people or dealing directly with the public. This includes serving customers in restaurants and stores, and receiving clients or guests’.

[4] *RDI* is defined as $RDI_i = \frac{1}{\sum_j E_{ij}/E_j}$ where E_{ij} represents employment in industry *j* in city *i* and E_j national employment in industry *j*.

[5] In our dataset diversified cities are as well larger than specialised cities, which is discussed in Sect. 11.4.2.

11.4 Data

11.4.1 Database Construction

We use individual wage data for 2009 provided by the Current Population Survey (CPS). For each individual it contains information on personal characteristics (education level, age, marital status etc.), occupation, industry, wage and location. Occupations are converted to a time-consistent scheme of 326 occupations (as in Autor and Dorn 2010). Our sample consists of working individuals living in Metropolitan Statistical Areas (MSAs) in 2009, aged between 16 and 65, working outside the agricultural sector. We exclude all self-employed workers. This results in a sample of 83,078 individuals.

Wages are measured by hour. Following Lemieux (2006), outliers are removed by trimming very small (hourly wage below $1) and very large values (hourly wage above $101) of wages. Hourly wages above $101 are top coded within the CPS and are therefore replaced with the 1.4 top coded value. For missing wage values we apply a no-imputation approach. The no-imputation method excludes the wages of missing cases but counts them when calculating occupational sizes (Mouw and Kallenberg 2010).

Communication job tasks and work activities are collected from the ONET Skill Survey. The ONET data characterizes the workers abilities, interest, knowledge, skills, work activities, work context and work values, by occupation. Three types of work activities and three work context items are included as communication job tasks. They measure the importance of:

- Establishing and maintaining interpersonal relationships (label “relations”)
- Communicating with persons outside organization (label “external communication”)
- Communicating with supervisors, peers, or subordinates (label “internal communication”)
- Face-to-Face discussions (label “Face-to-Face”)
- Work with work group or team (label “teamwork”)
- Contact with others (label “contact”)

Table 11.1 lists the ONET definition of these communication job tasks. We normalise the scores of these variables (mean 0 and standard deviation 1) to equalise scaling.[6] The communication job task scores of the occupations are matched to the occupations in the CPS database. A Communication-Index is estimated by using principal component analysis:

$$Y_i = \beta_i Communication + \varepsilon_i \tag{11.12}$$

[6] The section ‘Data Source’ in the Appendix provides insight in the original scaling of the variables, Table 11.14 present the correlations between the variables.

Table 11.1 Communication job tasks

	Definition by ONET	Correlation with wage
Relations	Developing constructive and cooperative working relationships with others, and maintaining them over time	0.34***
External communication	Communicating with people outside the organization, representing the organization to customers, the public, government, and other external sources	0.39***
	This information can be exchanged in person, in writing, or by telephone or e-mail	
Internal communication	Providing information to supervisors, co-workers, and subordinates by telephone, in written form, e-mail, or in person	0.35***
Face-to-face	How often do you have to have face-to-face discussions with individuals or teams in this job?	0.27***
Teamwork	How important is it to work with others in a group or team in this job?	0.14***
Contact	How much does this job require the worker to be in contact with others (face-to-face, by telephone, or otherwise) in order to perform it?	0.05***
Communication-Index	Principal-component index of the above six tasks	0.35***

Y is the constructed index based on the input of the six communication tasks represented by i. The estimates are presented in Table 11.15 in the section 'Variables' in the Appendix. The principal component loadings (β_i) could be viewed as weights and are rather equal for all communication tasks in the first component. The first component explains about 0.60 % of the total variation in the 6 tasks. The first component explains a substantial larger variation than the other components. Therefore, the first component is defined as the Communication-Index.

Employment figures are gathered from the Local Area Unemployment Statistics from the Bureau of Labor Statistics Additional. The employment figures include information on the total employment in the city and the employment by industry (which is used for the construction of the local specialisation level). Lastly, additional city data, such as average rents, are collected from the Census Decennial Database.

The appendix describes the data sources, the used classifications and includes a list of all the used variables, their measurement and sources.

11.4.2 Descriptive Statistics

Before we proceed to present a set of estimates, we first discuss the descriptive statistics. Table 11.2 provides an overview of the characteristics of our entire sample of 83,078 individuals. The average worker earns 22 US dollars per hour, is 40 years old and works in a city of almost 1.3 million employees. One out of two

Table 11.2 Summary statistics

	Mean	Standard deviation	Minimum	Maximum	Correlation with Communication Index
Hourly wage	21.9	16.26	2.49	230.6	0.35***
Communication Index	0.43	0.89	−3.11	2.46	1.00***
Specialisation-city	0.00	1.00	−1.46	3.74	−0.05***
Diversity-city	0.00	1.00	−2.17	1.69	0.02***
Employment-city	1,311,017	1,136,008	60,580	4,328,589	0.01***
Dominant industry	0.01	0.11	0.00	1.00	−0.03***
High-school drop-out	0.08	0.27	0.00	1.00	−0.31***
High-school	0.26	0.44	0.00	1.00	−0.28***
Some college	0.29	0.45	0.00	1.00	−0.02***
College graduate	0.37	0.48	0.00	1.00	0.44***
Communication job activities	2.55	0.98	1.00	4.83	0.33***
Non-white	0.21	0.41	0.00	1.00	−0.04***
Non-married	0.45	0.50	0.00	1.00	−0.11***
Age	4.00	12.44	16.00	64.00	0.10***
Female	0.52	0.50	0.00	1.00	0.14***

Note: Source Current Population Survey 2009, n = 81,262

workers is female. Individuals who perform more communication job tasks earn higher wages, live more often in diversified cities, are more often high educated and female.

The last column of Table 11.2 shows the correlations between the performance of the six communication job tasks and individual wages. All the correlations are positive and significant. The establishment of relations, communication outside the organisation and communication with workers inside the organisation show the strongest correlations with individual wages. The measure for contact in general only weakly correlates with wages. Cities which house many communication intensive occupations also obtain high average wages (correlation of 0.71, significant at the 1 % level, see Fig. 11.1). The relation between local wages and local communication, as predicted in Eq. (11.6) does hardly show any outliers. Ann Arbor has the most communication intensive labour market and is the sixth city on the wage ranking. Canton-Massillon has the least communication intensive labour market and only 17 of the 168 cities have a lower average wage than Canton-Massilon.

Equation (11.1) suggests that cities with a lower specialisation level benefit more from the performance of communication tasks. Indeed, workers in diversified cities perform on average more communication tasks, while workers in specialised cities perform less communication tasks (see Fig. 11.2). Given a certain level of diversity or specialisation, the variation in communication is however large between cities. On average, wages are also higher in diversified cities and lower in specialised cities (see Fig. 11.3). The appendix presents a correlation matrix of all variables.

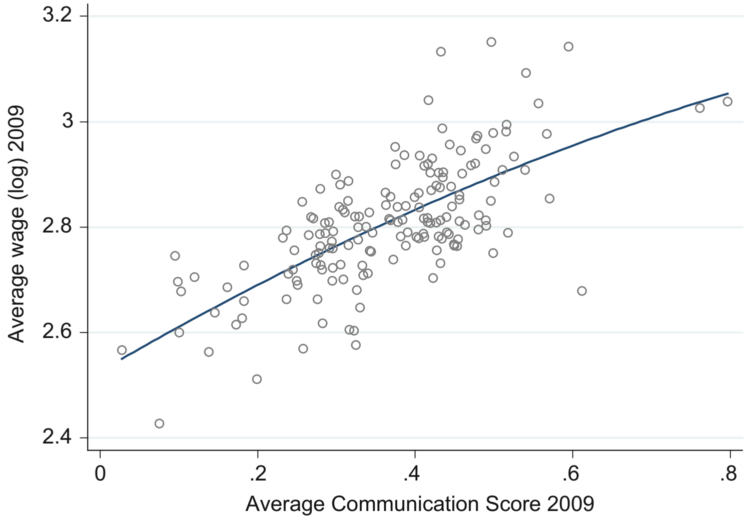

Fig. 11.1 Wages and communication in cities (Note: source Current Population Survey 2009. City level data, n = 168. The correlation is 0.71 (0.00) and significant at the 1 % level. Communication is measured as the average score on the Communication-Index as defined in Sect. 11.4. Wage is measured as average hourly wage 2009 in logs)

11.5 OLS-Estimates

Before we address causality, we present a set of OLS-estimates to show the relationship between wage and communication in a more rigorous way. Column 1 in Table 11.3 presents the estimates of a straightforward wage regression. We find the usual returns to education (e.g. as in Rauch 1993; Bacolod et al. 2009). Both industrial specialisation and diversity correlate negatively with individual wages. The positive correlation between local diversity and individual wage (as found in Sect. 11.4.2) turns negative when we control for demographic and educational factors. Workers who work in the dominant local industry (M in Eq. (11.11)) earn substantially more than workers who do not work in the dominant industry. This effect increases with the specialisation level of the city. Notable is the positive impact of rents on wages which indicates the cities' role of centres for consumption (Glaeser et al. 2001). All the covariates, such as age and gender, obtain the expected sign and size.

Next, we test whether the correlations between wages and communication vary with the industrial specialisation and diversity level of the city. Column (2) includes a cross-term between communication and the local specialisation level (all variables are standardised to ease comparison). The coefficient of the cross-term is negative and significant: the correlation between wage and performed communication tasks is weaker in specialised cities. The linear impact of communication remains positive and significant, while the size of the coefficient of local specialisation

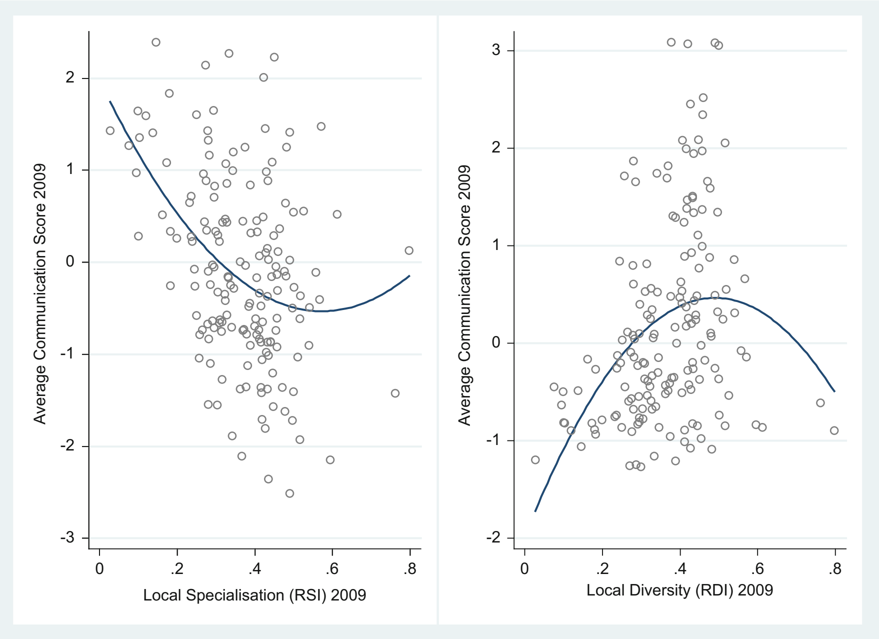

Fig. 11.2 Communication in specialised and diversified cities (Note: source Current Population Survey 2009. City level data, n = 168. The correlations are respectively −0.40 (0.00) and 0.33 (0.00) and significant at the 1 % level. *RSI* and *RDI* are measured as described in Sect. 11.3. Communication is measured as the average score on the Communication-Index as defined in Sect. 11.4)

decreases. Column (3) performs the same regression but includes a cross-term between communication and sector diversity instead of sector specialisation. The coefficient of the cross-term is positive and significant. Both in specialised and in diversified cities workers in communication intensive jobs earn more, but this relation is stronger in diversified cities and weaker in specialised cities.

Lastly, we allow the relation between wages and communication to vary across city size. Diversified cities are on average larger than specialised cities. Column (5) presents the baseline results including city size instead of industrial structure and column (6) presents the results including the cross-term as well. The correlations between wage and performed communication tasks are stronger in larger cities. Workers in larger cities who perform communication tasks earn more than workers in small cities with the same task package. The positive coefficient of the cross-term between city size and communication outweighs the negative linear coefficient for communication.

Similar to the theory of Sect. 11.2, individual wages increase with the ability of the worker, the communication of the worker when the local industry is not so specialised and the specialisation level when the worker works in the dominant industry. The OLS-estimates suggest that one standard deviation more

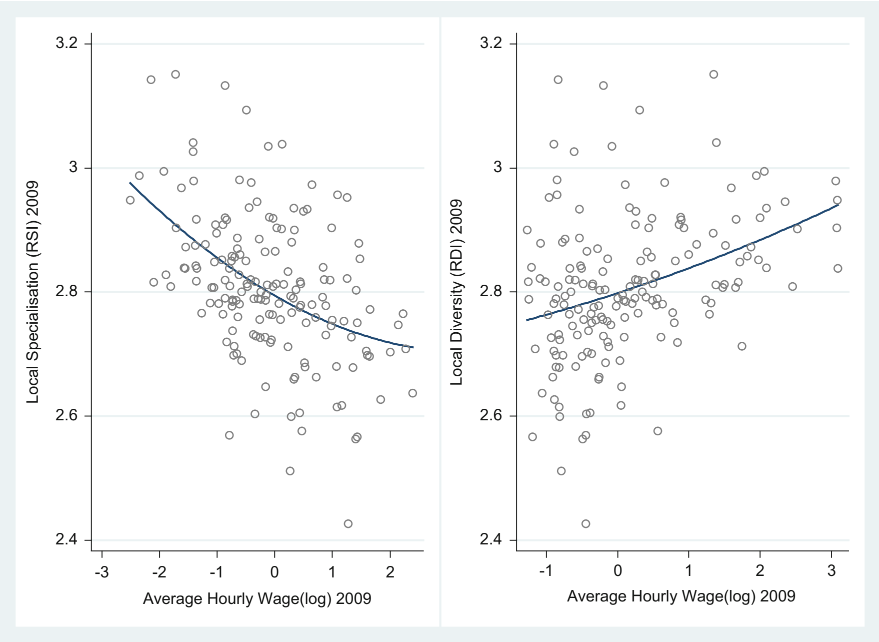

Fig. 11.3 Wages in specialised and diversified cities (Note: source Current Population Survey 2009. City level data, n = 168. The correlations are respectively −0.46 (0.00) and 0.36 (0.00) and significant at the 1 % level. *RSI* and *RDI* are measured as described in Sect. 11.3. Wage is measured as average hourly wage 2009 in logs)

communication job tasks increases wages with about 16 % of a standard deviation. In specialised cities this is 13 % of a standard deviation, in diversified cities 18 % of a standard deviation and 20 % in large cities.

11.6 IV-Estimates

The main issue with OLS wage estimates is a possible omitted ability bias. Equation (11.1) distinguishes between an ability and a productivity effect. This distinction is hampered if workers in highly productive cities or jobs are simply ‘better’ in an unobserved way. Ability characteristics such as talent, work discipline and ambition are unobserved in our analyses. For instance, relatively talented workers might be attracted to certain cities. Diversified cities tend to be larger and house more amenities than the smaller, specialised cities. Talented workers could value these amenities more than less talented workers. Talent of workers is however not measured. In OLS-estimates the higher wages within these cities are assigned to higher local productivity of these cities while they might simply reflect higher (unobserved) ability levels. The same feature might bias the impact of

Table 11.3 Returns to communication, specialised and diversified cities (OLS)

	Dependent: individual wage (log)					
	(1)	(2)	(3)	(4)	(5)	(6)
Communication		0.098***	0.099***	0.098***		0.098***
		[0.019]	[0.019]	[0.019]		[0.019]
COM*specialisation			−0.019***			
			[0.004]			
COM*diversity				0.010***		
				[0.003]		
COM*size						0.023***
						[0.004]
Specialisation	−0.038***	−0.038***	−0.030***	−0.038***		
	[0.004]	[0.004]	[0.004]	[0.004]		
Diversity	−0.009**	−0.009***	−0.009**	−0.014***		
	[0.004]	[0.004]	[0.003]	[0.004]		
Size					0.043***	0.035***
					[0.004]	[0.003]
Dominant industry	0.105***	0.118***	0.115***	0.119***	0.107***	0.120***
	[0.026]	[0.023]	[0.023]	[0.023]	[0.026]	[0.020]
DOM*specialisation	0.066***	0.065***	0.057***	0.060***	0.047***	0.039**
	[0.018]	[0.018]	[0.017]	[0.017]	[0.017]	[0.017]
Drop-out	−0.204***	−0.185***	−0.183***	−0.185***	−0.204***	−0.181***
	[0.013]	[0.014]	[0.014]	[0.014]	[0.014]	[0.014]
College	0.080***	0.069***	0.069***	0.069***	0.080***	0.070***
	[0.008]	[0.008]	[0.008]	[0.008]	[0.008]	[0.008]
College grad	0.363***	0.348***	0.347***	0.348***	0.373***	0.357***
	[0.021]	[0.020]	[0.020]	[0.020]	[0.021]	[0.020]
Rent	0.046***	0.047***	0.047***	0.047***		
	[0.003]	[0.003]	[0.003]	[0.003]		

(continued)

Table 11.3 (continued)

	Dependent: individual wage (log)					
	(1)	(2)	(3)	(4)	(5)	(6)
Communication job	−0.018	−0.041***	−0.041***	−0.041***	−0.018	−0.041***
	[0.015]	[0.013]	[0.013]	[0.013]	[0.015]	[0.013]
Non-white	−0.085***	−0.082***	−0.082***	−0.082***	−0.062***	−0.061***
	[0.008]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]
Non-married	−0.056***	−0.055***	−0.056***	−0.055***	−0.055***	−0.055***
	[0.007]	[0.006]	[0.006]	[0.006]	[0.007]	[0.006]
Age	0.049***	0.048***	0.049***	0.048***	0.050***	0.049***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Age squared	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Female	−0.184***	−0.183***	−0.183***	−0.183***	−0.185***	−0.184***
	[0.014]	[0.013]	[0.013]	[0.013]	[0.014]	[0.013]
Occupation dummies	YES***	YES***	YES***	YES***	YES***	YES***
Observations	82,705	82,705	82,705	82,705	81,262	81,262
R-squared	0.438	0.445	0.446	0.445	0.433	0.440

Note: Individual data. Communication represents the Communication-Index as defined in Sect. 11.4. Specialisation refers to the *RSI*, diversity to the *RDI* as defined in Sect. 11.3. City size is measures in standardised logs. Dominant industry is a dummy variable indicating whether the worker works in the local dominant industry or not. The dominant local industry obtains the highest specialisation level. High-school graduates are the reference group for education. Communication job refers to the importance of communication work activities in the job as defined in Sect. 11.4. See The appendix for a detailed description of the variables, measurement and data sources. Regressions also include a constant. Clustered standard errors in parentheses, *significant at the 10 % level, **significant at the 5 % level, ***significant at the 1 % level communication on wage. It could be the case that communication intensive jobs offer more carrier opportunities in the long run. Workers with a relatively high ambition are more likely to sort into these jobs. In the OLS-estimates, the high wages of these jobs are related to the communication intensity while the impact of worker ambition is unobserved. Combes et al. (2009) refer to this issue as the ‘endogenous quality of labour’ problem.

11.6.1 Instruments

11.6.1.1 Communication

We construct a language-skill proxy as an instrument for communication job tasks.[7] We assume workers with weaker language-skills to be less likely to perform communication job tasks. Transformation of tacit knowledge is key to communication job tasks and strongly affected by language-skills. Language-skills are proxied by information on the country of birth of the worker and the parents of the worker. The country of birth indicates the mother-tongue of the worker. We assume workers who grew up in an English speaking household to obtain better language-skills (in the US) than workers who grew up in a non-English speaking household. The language-skill proxy obtains four values which are described in Table 11.12 in the appendix.

Our instrument should be exogenous and not affecting wage via other channels than communication. Clearly, the country of birth is not chosen by the individual and is exogenous. However, we do not observe the actual household language which might be endogenous. We assume such an effect to be negligible. Another possible issue with the proxy is that it might capture the sorting of migrants into certain cities. Figures 11.4 and 11.5 in the appendix present the relations between city’s specialisation level, diversity level and communication level and the average native share in local occupations. The proxy does not seem to capture such sorting patterns.

Language-skills may affect wages via other channels than communication. For instance, the language-skill proxy captures cultural differences which could affect wage as well. Lewis (2011) finds that this effect is rather small. We test the validity of the instrument in Table 11.4. The first column shows a wage regression including

[7] Charlot and Duranton (2004) instrument communication job tasks with the use of computers and internet at the work floor. The Current Population Survey includes similar information for the year 2000. However, we cannot rule out possible endogeneity of computer use. Workers may sort by ability into communication and computer intensive jobs for the same reasoning. Specification tests underline that computer use at the job is endogenous.

Table 11.4 Instrumental variables are valid

	OLS-estimates			IV-estimates: first stage		IV-estimates: second stage	
	Wage (1)	Communication (2)	Physical (3)	Communication (4)	Physical (5)	Communication (6)	Physical (7)
Communication	0.096***	0.098***				0.109***	
	[0.023]	[0.019]				[0.042]	
Language-skill proxy	0.006			0.434***	0.008		
	[0.021]			[0.097]	[0.072]		
Physical			−0.058*				5.837
			[0.031]				[52.293]
Specialisation	−0.038***	−0.038***	−0.037***	−0.001	0.016**	−0.038***	−0.132
	[0.004]	[0.004]	[0.004]	[0.004]	[0.007]	[0.004]	[0.859]
Diversity	−0.009***	−0.009***	−0.009**	0.003	0.007	−0.009***	−0.051
	[0.004]	[0.004]	[0.004]	[0.003]	[0.006]	[0.004]	[0.385]
Dominant industry	−0.184***	−0.185***	−0.201***	−0.050**	0.056**	−0.183***	−0.517
	[0.014]	[0.014]	[0.013]	[0.023]	[0.022]	[0.015]	[2.891]
DOM*specialisation	0.069***	0.069***	0.079***	0.063***	−0.022	0.068***	0.202
	[0.008]	[0.008]	[0.009]	[0.016]	[0.023]	[0.009]	[1.117]
Drop-out	0.348***	0.348***	0.351***	0.108***	−0.212***	0.346***	1.594
	[0.020]	[0.020]	[0.019]	[0.029]	[0.044]	[0.021]	[11.041]
College	−0.041***	−0.041***	−0.014	0.175***	0.060	−0.043**	−0.373
	[0.013]	[0.013]	[0.015]	[0.051]	[0.070]	[0.017]	[3.293]
College grad	0.047***	0.047***	0.046***	−0.002	−0.007**	0.047***	0.090
	[0.003]	[0.003]	[0.003]	[0.003]	[0.004]	[0.003]	[0.389]
Rent	0.119***	0.118***	0.100***	−0.086**	−0.080	0.120***	0.577
	[0.023]	[0.023]	[0.028]	[0.039]	[0.055]	[0.024]	[4.205]
Communication job	0.064***	0.065***	0.068***	−0.022	0.041	0.065***	−0.174
	[0.018]	[0.018]	[0.018]	[0.037]	[0.042]	[0.018]	[2.179]
Non-white	−0.081***	−0.082***	−0.084***	−0.004	0.015	−0.081***	−0.170
	[0.007]	[0.007]	[0.008]	[0.016]	[0.016]	[0.007]	[0.846]

Non-married	−0.055***	−0.055***	−0.056***	−0.014	0.006	−0.055***	−0.090
	[0.006]	[0.006]	[0.006]	[0.009]	[0.011]	[0.006]	[0.301]
Age	0.049***	0.048***	0.049***	0.010**	−0.006	0.048***	0.084
	[0.003]	[0.003]	[0.003]	[0.004]	[0.006]	[0.003]	[0.306]
Age squared	−0.000***	−0.000***	−0.000***	−0.000**	0.000	−0.000***	−0.001
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.004]
Female	−0.183***	−0.183***	−0.182***	−0.027	0.043	−0.182***	−0.435
	[0.013]	[0.013]	[0.013]	[0.032]	[0.052]	[0.013]	[2.255]
Occupation dummies	YES***	YES***	YES***	YES***	YES***	YES***	YES***
Observations	82,705	82,705	82,705	82,705	82,705	82,705	82,705
R-squared	0.445	0.445	0.441	0.736	0.626	0.445	
F-test				19.81	0.01		

Note: Individual data. See The appendix for a detailed description of the variables, measurement and data sources. Regressions also include a constant. Clustered standard errors in parentheses, *significant at the 10 % level, **significant at the 5 % level, ***significant at the 1 % level both communication job tasks and the language-skill proxy. After controlling for communication, the language-skill proxy does not affect wage. Columns (2) and (3) show the OLS-estimates for communication and physical job tasks. Physical tasks are defined as 'handling and moving objects' and correlate negatively with wage. The next two columns (4 and 5) show the first stage results for IV-estimates instrumenting respectively communication and physical job tasks with the language-skill proxy. The proxy correlates strongly with communication jobs tasks and not with physical job tasks. Columns (6) and (7) present the IV-estimates. The IV-estimates for communication (column (6)) correspond with the OLS-estimates. The IV-estimates for physical tasks are insignificant. The significant wage effect of physical tasks diminishes in the IV-estimates. These results indicate that our language-skill proxy does not measure a cultural wage effect.

11.6.1.2 Specialisation and Diversity

Ciccone and Hall (1996) introduced the standard way to tackle the endogeneity problem of city size and productivity. The spatial population distribution in the US is (to some extent) persistent over time. The division of employment across cities is remarkably constant. Thus, the size of a city today can be predicted by the size of the city many decades ago. Today's main drivers of productivity strongly differ from the historical drivers. Thus, historical population of a city strongly correlates with today's city size but does not affect the current wages in the city. Clearly, today's wages cannot affect historical city population. This makes historical population a valid instrument for current city size, at least when the instrument is measured in the far past. For an extensive discussion on the validity and exogeneity of historical population as an instrument we refer to the work of Ciccone and Hall (1996) and Combes et al. (2009).

The sectoral specialisation and diversity of cities is correlated with size (respectively −0.66 and 0.57, significant at the 1 % level). Therefore, we instrument sectoral specialisation and diversity with population in 1930.

The MSA population in 1930 is composed using Census Historical County Population figures. For each county this database includes decennial information on its population. We include population in 1930 as this is the first year with a decent covering across counties. Next, we sum county population by MSA (1990 definition) to construct MSA population in 1930. The MSA population in 1930 varies between 9,897 and 7,524,736 inhabitants.

11.6.2 Relevance of the Instruments

Before we turn to the IV-estimates we test the relevance of our instruments. The correlation between population in 1930 and sectoral specialisation in 2009 is −0.51 and significant at the 1 % level. For sectoral diversity this correlation is 0.61

(significant at the 1 % level). Also the instrument of communication is strongly correlated with the communication index (0.58, significant at the 1 % level).

Columns (1) and (2) of Table 11.5 show the first stage estimates for communication job tasks. In column (1) we include the city's sectoral specialisation and diversity level as explanatory variables while in column (2) we include city's population in 1930. The language-skill proxy seems to be a sound instrument for communication. Natives are relatively more present in communication-intensive occupations. The covariates show the usual sign and coefficients. By definition, the communication intensity of occupations does not vary across cities which explain the insignificant coefficients of historical and sectoral structure.[8] Communication work activities (waiting tables e.g.) and communication job tasks (communicating about work activities) are positively correlated. The F-statistics show that the instrument for communication is valid.[9] Columns (3) and (4) present the first stage results for sectoral specialisation, with and without instrumenting communication as well. To produce interpretable results, we include the log of historical population. Historical city size is a decent predictor for current sectoral specialisation. The F-statistics indicate that historical population is a valid instrument for current specialisation level. Lastly, columns (5) and (6) show the first stage estimates for the industrial diversity level of cities. Historical city size predicts current sectoral diversity even more precise than it predicts current sectoral specialisation. In diversified cities, workers perform more communication work activities while communication about these activities is indifferent from the average.

11.6.3 Results

Table 11.6 presents the IV-estimates. As in Table 11.3 the returns to communication are allowed to vary with city specialisation level, diversity level and city size. For each city characteristic (specialisation, diversity and size) we first present the baseline regression in which communication is instrumented with our language-skill proxy and the characteristic with population in 1930. The next column shows the IV-estimates with additional cross-terms between the language-skill proxy and the city characteristics. The IV-estimates provide similar results as the OLS-estimates.

The returns to communication remain positive and significant. An increase of the communication job tasks of one standard deviation raises the individual wage with about 18 % of a standard deviation. The returns to communication are about 16 % of a standard deviation in specialised cities (column (2)).

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[8] The importance of communication is measured at the occupation level and independent of location.

[9] F-statistics are generated for the additional instruments only (communication and population in 1930).

Table 11.5 First stage regressions

	Communication		Specialisation		Diversity	
	(1)	(2)	(3)	(4)	(5)	(6)
Language-skill proxy	0.434***	0.434***		0.010		−0.013
	[0.097]	[0.097]		[0.013]		[0.008]
Population 1930		0.001	−0.372***	−0.372***	0.477***	0.477***
		[0.002]	[0.005]	[0.005]	[0.003]	[0.003]
Communication			−0.003		0.006	
			[0.011]		[0.007]	
Specialisation	−0.001					
	[0.004]					
Diversity	0.003					
	[0.003]					
Dominant industry	−0.086**	−0.088**	−0.214***	−0.212***	−0.580***	−0.582***
	[0.039]	[0.039]	[0.068]	[0.068]	[0.059]	[0.058]
DOM*specialisation	−0.022	−0.023	0.845***	0.845***	0.135*	0.136*
	[0.037]	[0.039]	[0.036]	[0.036]	[0.072]	[0.071]
Drop-out	−0.050**	−0.050**	−0.023	−0.020	−0.023	−0.028*
	[0.023]	[0.023]	[0.015]	[0.014]	[0.015]	[0.015]
College	0.063***	0.063***	0.041***	0.040***	0.021***	0.023***
	[0.016]	[0.016]	[0.009]	[0.009]	[0.007]	[0.007]
College grad	0.108***	0.109***	−0.035***	−0.036***	−0.009	−0.007
	[0.029]	[0.029]	[0.010]	[0.010]	[0.015]	[0.015]
Communication job	0.175***	0.175***	−0.000	−0.003	0.016***	0.020***
	[0.051]	[0.051]	[0.007]	[0.007]	[0.006]	[0.006]
Rent	−0.002	−0.001	−0.277***	−0.277***	0.051***	0.051***
	[0.003]	[0.003]	[0.006]	[0.006]	[0.005]	[0.005]
Non-white	−0.004	−0.004	−0.162***	−0.161***	−0.101***	−0.102***
	[0.016]	[0.016]	[0.010]	[0.010]	[0.010]	[0.010]
Non-married	−0.014	−0.014	−0.040***	−0.040***	−0.014**	−0.014**
	[0.009]	[0.009]	[0.008]	[0.008]	[0.007]	[0.007]
Age	0.010**	0.010**	−0.007***	−0.007***	0.004**	0.004**
	[0.004]	[0.004]	[0.002]	[0.002]	[0.002]	[0.002]
Age squared	−0.000**	−0.000**	0.000***	0.000***	−0.000*	−0.000*
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Female	−0.027	−0.027	0.023***	0.023***	−0.012	−0.012
	[0.032]	[0.032]	[0.008]	[0.008]	[0.007]	[0.007]
Occupation dummies	YES***	YES***	YES***	YES***	YES***	YES***
Observations	82,705	82,705	82,705	82,705	82,705	82,705
R-squared	0.736	0.736	0.365	0.365	0.383	0.383

Note: Individual data. See The appendix for a detailed description of the variables, measurement and data sources. F-test for additional instruments communication and population 1930. Regressions also include a constant. Clustered standard errors in parentheses, *significant at the 10 % level, **significant at the 5 % level, ***significant at the 1 % level

Table 11.6 IV-estimates

Dependent: individual wage (log)	Specialisation		Diversity		Size	
	(1)	(2)	(3)	(4)	(5)	(6)
Communication	0.110***	0.108***	0.110***	0.110***	0.108***	0.106**
	[0.042]	[0.041]	[0.042]	[0.042]	[0.042]	[0.042]
COM*specialisation		−0.015***				
		[0.005]				
COM*diversity				0.006		
				[0.005]		
COM*size						0.027***
						[0.007]
Specialisation	−0.055***	−0.047***	−0.033***	−0.033***		
	[0.010]	[0.009]	[0.004]	[0.004]		
Diversity	−0.017***	−0.016***	0.000	−0.002		
	[0.005]	[0.005]	[0.005]	[0.005]		
Size					0.022***	0.012**
					[0.004]	[0.005]
Dominant industry	−0.184***	−0.183***	−0.183***	−0.183***	−0.185***	−0.181***
	[0.015]	[0.015]	[0.015]	[0.015]	[0.015]	[0.015]
DOM*specialisation	0.069***	0.069***	0.067***	0.068***	0.066***	0.066***
	[0.008]	[0.009]	[0.009]	[0.009]	[0.009]	[0.009]
Other controls	YES***	YES***	YES***	YES***	YES***	YES***
Observations	82,705	82,705	82,705	82,705	81,262	81,262
R-squared	0.444	0.445	0.444	0.445	0.445	0.446

Note: Individual data. City size is instrumented by population in 1930. Communication is instrumented by language-skill proxy. Cross-terms are interactions of instruments. Regressions include controls for dominant industry, a cross-term of dominant industry with specialisation, education dummies, communication work activities, age, age squared, gender, marital status, occupational dummies and a constant. See The appendix for a detailed description of the variables, measurement and data sources. Clustered standard errors in parentheses, *significant at the 10 % level, **significant at the 5 % level, ***significant at the 1 % level

In large cities the returns to communication are somewhat higher (about 21 %, column (6)). The coefficient of the cross-term between communication and diversity level becomes insignificant (column (4)). Especially in large, not specialised cities workers earn more when they perform more communication tasks.

The variation in returns to communication between different city types partly explains the lower wages in specialised cities. The negative specialisation wage premium decrease from 9 % of a standard deviation to 8 %. The urban wage premium decrease from 4 % of a standard deviation to 2 % of a standard deviation.

11.7 Robustness

We test the robustness of our estimates by considering four robustness checks. Here, we only present the IV-estimates including the cross-term between communication job tasks and local specialisation level. The OLS-estimates and IV-estimates including the other cross-terms provide similar results and are available upon request. First, we test the sensitivity of the results towards the measure of communication (Sect. 11.7.1). Second, Sect. 11.7.2 discusses an additional test for the impact of unobserved ability. Next, we add cross-terms between communication and individual skill level to our analyses (Sect. 11.7.3). Lastly, the measure of local specialisation level is put to the test (Sect. 11.7.4).

11.7.1 Other Measures of Communication

To address the validity of our results we test three alternative ways to measure communication job tasks. First, we measure communication job tasks as the share of all job tasks. This indicator measures the importance of communication relative to other job tasks instead of the absolute importance of communication. Columns (1) and (2) in Table 11.7 presents the IV-estimates. The relative returns to communication are significantly larger than the absolute returns to communication. An increase of one standard deviation in relative communication leads to an increase of 41 % of a wage standard deviation. Within specialised cities this return is only 32 % of a standard deviation. The returns to communication do not differ across local diversifications level while the returns in large cities are 52 % of a standard deviation.

Second, we consider the wage returns to non-routine interactive tasks. Information and communication technology (ICT) acts as a substitute for some tasks and a complement for others (e.g. Autor et al. 2003). Computer technology replaces labour in performing routine tasks that can easily be described with programmed rules, such as the repetitive tasks of clerks and cashiers (Bresnahan 1999). On the other hand, non-routine tasks, such as managing others, legal writing and selling, cannot, as of yet, be described as a set of programmable rules. Non-routine tasks

Table 11.7 Other measures of communication – IV-estimates

	Dependent: individual wage (log)					
	Relative communication		Non-routine interactive		People skills	
	(1)	(2)	(3)	(4)	(5)	(6)
Communication	0.264**	0.259**	0.162**	0.160**	0.133***	0.131***
	[0.132]	[0.131]	[0.077]	[0.077]	[0.049]	[0.049]
COM*specialisation		−0.047***		−0.023***		−0.019***
		[0.016]		[0.008]		[0.006]
Specialisation	−0.049***	−0.005	−0.058***	−0.057***	−0.052***	−0.042***
	[0.010]	[0.020]	[0.011]	[0.011]	[0.010]	[0.010]
Diversity	−0.013***	−0.012**	−0.018***	−0.017***	−0.015***	−0.014***
	[0.005]	[0.005]	[0.006]	[0.006]	[0.005]	[0.005]
Dominant industry	0.104***	0.099***	0.122***	0.120***	0.114***	0.110***
	[0.024]	[0.024]	[0.030]	[0.029]	[0.030]	[0.030]
DOM*specialisation	0.086***	0.080***	0.080***	0.075***	0.081***	0.073***
	[0.020]	[0.019]	[0.021]	[0.021]	[0.021]	[0.021]
Other controls	YES***	YES***	YES***	YES***	YES***	YES***
Observations	82,705	82,705	82,705	82,705	82,705	82,705
R-squared	0.413	0.414	0.412	0.412	0.435	0.436

Note: Individual data. Relative communication is the importance of communication relative to all other work activities and work context. Non-routine interactive tasks are measured as in Acemoglu and Autor (2011). Regressions include controls for dominant industry, a cross-term of dominant industry with specialisation, education dummies, communication work activities, age, age squared, gender, marital status, occupational dummies and a constant. See The appendix for a detailed description of the variables, measurement and data sources. Clustered standard errors in parentheses, *significant at the 10 % level, **significant at the 5 % level, ***significant at the 1 % level require an adaptive attitude of the worker; these are typically tasks involving communication, interaction and knowledge transfer. The rival effects of computer technology on routine tasks on the one hand and non-routine on the other hand relate to the rival spatial effects of technology as indicated by Glaeser and Ponzetto (2007), Gaspar and Glaeser (1998) and Ioannides et al. (2008). Autor and Dorn (2010) show that cities with initially specialisation in routine-intensive occupations obtain employment and wage polarization after 1980. Clearly, non-routine interactive and communication tasks are strongly related (0.72, significant at the 1 % level). The first stage regression shows a strong correlation between the language-skills proxy and the non-routine interactive tasks of an occupation[10]. Columns (3) and (4) of Table 11.7 present the IV-estimates with the linear and cross-terms of non-routine interactive tasks instead of communication job tasks. The IV-estimates indicate a positive return to the performance of non-routiness interactive tasks of about 25 % of a standard deviation. This return is - as expected - somewhat lower in specialised cities (about 21 % of a standard deviation) and somewhat higher in diversified cities (about 30 % of a standard deviation).

The last measure of communication stems from the work of Borghans et al. (2006) and Bacolod et al. (2009) and measures the interpersonal skill requirements of the job: the importance of ‘people skills’. We calculate the importance of ‘people skills’ by the importance of six ONET skill variables: social perspectives, coordination, persuasion, negotiation, instruction and service orientation. The last three columns of Table 11.7 present the results. Including people skills instead of communication job tasks does not change the results. There are positive wage returns to the performance of people skills in cities, these returns increase with the size of city and decrease with the specialisation level of the city.

11.7.2 *Unobserved Ability*

Sorting of workers by unobserved ability is a commonly acknowledged measurement issue for spatial wage estimations (e.g. Combes et al. 2008). Ideally, we would eliminate unobserved worker heterogeneity using a large panel of individuals. The CPS is not a panel but has a time dimension. We aggregate the individual data to the city level (MSA) to obtain a panel of cities. Additionally to our IV-estimates we take the first difference of local variables and remove the unobserved ability bias using the time dimension.

As discussed in Sect. 11.3.2, unobserved ability (A_k) could cause biased estimates when it correlates with other explanatory variables. We assume that unobserved ability A_k (such as personal talent, ambition and work discipline) is

[10] The index is defined as in Acemoglu and Autor (2011). The index is standardised with mean 0 and standard deviation 1. Data The appendix describes the measurement of this index.

time invariant. Taking the first difference removes the eventual ability bias. To do so, we add a time dimension to Eq. (11.11):

$$\ln w_{kit} = \alpha_1 + \alpha_2\hat{\varphi}_k + \alpha_3\hat{M}_{kt} + \beta_1\hat{\theta}_{kt} + \beta_2\hat{\rho}_{it} + \beta_3\hat{R}_{it} + \gamma_1(\hat{\theta}_{kt}\cdot\hat{\rho}_{it}) + \gamma_2(\hat{M}_{kt}\cdot\hat{\rho}_{it}) + \varepsilon_{kit} \tag{11.13}$$

Individual ability $(\hat{\varphi}_k)$ is constant over time t. The amount of communication tasks the worker performs $(\hat{\theta}_{kt})$, the specialisation level $(\hat{\rho}_{it})$ and the size of the city $(\hat{R}_{it})$ might change over time. The measurement error includes the ability of worker k (A_k which is constant over time and place) and some measurement error at the individual, city, time level (μ_{kit}): $\varepsilon_{ki} = A_k + \mu_{ki}$.

To obtain a panel of cities we aggregate all indicators to the city level i:

$$\Delta\ln w_{ki} = \alpha_2\hat{\varphi}_i + \alpha_3\Delta\hat{M}_i + \beta_1\Delta\hat{\theta}_i + \beta_2\Delta\hat{\rho}_i + \beta_3\Delta\hat{R}_i + \gamma_1(\Delta\hat{\theta}_i\cdot\Delta\hat{\rho}_i) + \gamma_2(\Delta\hat{M}_i\cdot\Delta\hat{\rho}_i) + \Delta\varepsilon_i \tag{11.14}$$

in which $\Delta\varepsilon_i$ does not include unobserved ability. Table 11.8 presents the estimates of this model for the period 2006–2009. The results hold for several time periods. The estimates resemble the IV-estimates. The change in communication tasks at the MSA level between 2006 and 2009 is positively related with the change in MSA wage. The coefficients of the cross-term with sector specialisation is negative and significant, the cross-term with diversity in significant and the cross-term with size positive and significant.

11.7.3 Skill Level

Especially the spatial clustering of high skilled workers relates to higher local wages (Glaeser and Mare 2001; Glaeser and Gottlieb 2009). Skilled workers cluster in certain cities (e.g. New York, San Francisco) and these cities tend to be the ones with higher wages (Rauch 1993) and higher growth rates (Glaeser et al. 1995). Table 11.5 showed strong correlations between the sectoral structure of cities and the skill level of their inhabitants. Do high-skilled workers benefit more from performing communication tasks than low-skilled workers? The first two columns of Table 11.9 present the IV-estimates including cross-terms between communication and educational dummies. The cross-terms are insignificant while our variables of interest are hardly affected by the inclusion of these additional explanatory variables.

Table 11.8 First differences at MSA level

	Dependent: change in average MSA wage (2006–2009)				
	(1)	(2)	(3)	(4)	(5)
Communication		0.086***	0.069***		0.062***
		[0.015]	[0.017]		[0.017]
COM*specialisation		−0.030***			
		[0.005]			
COM*diversity			0.012		
			[0.009]		
COM*size					0.018**
					[0.008]
Specialisation	−0.055***	−0.043***	−0.055***		
	[0.002]	[0.002]	[0.001]		
Diversity	−0.010***	−0.011***	−0.016***		
	[0.002]	[0.002]	[0.004]		
Size				−0.005	0.040***
				[0.008]	[0.004]
Dominant industry	0.042	0.099	0.072	0.579**	0.144**
	[0.078]	[0.068]	[0.070]	[0.241]	[0.060]
DOM*specialisation	0.132**	0.111**	0.122**	−0.372**	0.070*
	[0.053]	[0.047]	[0.049]	[0.163]	[0.041]
Drop-out	−0.279***	−0.243***	−0.253***	−0.172**	−0.250***
	[0.027]	[0.024]	[0.024]	[0.083]	[0.022]
College	0.094***	0.095***	0.096***	0.086	0.087***
	[0.019]	[0.016]	[0.017]	[0.059]	[0.015]
College grad	0.378***	0.378***	0.377***	0.429***	0.369***
	[0.023]	[0.020]	[0.021]	[0.072]	[0.019]
Rent	−0.024	−0.030*	−0.027	−0.061	−0.029**
	[0.018]	[0.016]	[0.016]	[0.057]	[0.015]
Communication job	−0.073***	−0.073***	−0.070***	−0.026	−0.076***
	[0.016]	[0.014]	[0.015]	[0.051]	[0.013]
Non-white	0.009***	0.009***	0.009***	0.004**	0.009***
	[0.001]	[0.001]	[0.001]	[0.002]	[0.000]
Non-married	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Age	−0.192***	−0.202***	−0.202***	−0.276***	−0.202***
	[0.024]	[0.021]	[0.022]	[0.077]	[0.019]
Age square	0.328***	0.247***	0.256***	0.385***	0.265***
	[0.032]	[0.037]	[0.039]	[0.103]	[0.034]
Female	0.241***	0.177***	0.180***	0.348***	0.200***
	[0.036]	[0.038]	[0.040]	[0.113]	[0.035]
Occupation dummies	YES***	YES***	YES***	YES***	YES***
Observations	165	165	165	165	165
R-squared	0.981	0.986	0.985	0.807	0.988

Note: City data (aggregated individual data). See The appendix for a detailed description of the variables, measurement and data sources. Clustered standard errors in parentheses, *significant at the 10 % level, **significant at the 5 % level, ***significant at the 1 % level

Table 11.9 Additional variation: skill levels, industry and services. IV-estimates

	Dependent: individual wage (log)			
	Skill cross-terms		Manufacturing	Services
	(1)	(2)	(3)	(4)
Communication	0.114***	0.113***	0.182***	0.125***
	[0.036]	[0.036]	[0.055]	[0.047]
COM*specialisation		−0.016***	−0.069***	−0.015
		[0.005]	[0.021]	[0.009]
COM*drop-out	−0.002	−0.003		
	[0.006]	[0.005]		
COM*college	0.001	0.001		
	[0.007]	[0.007]		
COM*college grad	−0.013	−0.015		
	[0.041]	[0.041]		
Specialisation	−0.055***	−0.048***	−0.037***	
	−0.047***	[0.010]	[0.010]	[0.008]
[0.006]				
Diversity	−0.017***	−0.016***	−0.002	0.001
	[0.005]	[0.005]	[0.003]	[0.017]
Dominant industry	0.114***	0.111***	0.120***	0.124***
	[0.023]	[0.023]	[0.023]	[0.024]
DOM*specialisation	0.081***	0.073***	0.058***	0.065***
	[0.020]	[0.019]	[0.018]	[0.019]
Other controls	YES***	YES***	YES***	YES***
Observations	82,705	82,705	82,705	82,705
R-squared	0.443	0.444	0.446	0.445

Note: Individual data. All variables are standardized with mean 0 and standard deviation 1. Regressions include controls for dominant industry, a cross-term of dominant industry with specialisation, education dummies, communication work activities, age, age squared, gender, marital status, occupational dummies and a constant. See The appendix for a detailed description of the variables, measurement and data sources. Clustered standard errors in parentheses, *significant at the 10 % level, **significant at the 5 % level, ***significant at the 1 % level

11.7.4 Industrial Structure

Lastly, we test the sensitivity of the results to changes in the measure of the local industrial structure. The bias in the classification of sectors might hamper the estimates of our indicators for the local industrial specialisation and diversity level. Overall, manufacturing sectors are defined at a more detailed level in the classification than service sectors. A diverse local structure of manufacturing sectors therefore obtains a higher *RDI* than a diverse local structure of service sectors. Indeed, the variation in specialisation and diversity in manufacturing sectors is larger than the variation in service sectors. The last column of Table 11.9 present IV-estimates in which only manufacturing sectors (column 3) and only service sectors (column 4) are included in the *RSI*. The returns to communication job tasks vary with the local specialisation level of both manufacturing and service sectors. As expected, the variation in the local manufacturing specialisation obtains a stronger impact than the variation in the local service sector.

11.8 Conclusion

The debate in the empirical literature and economic regional policy has been largely about stimulating fruitful environments. The success of clusters like Silicon Valley and diversified cities such as New York City stimulated many scientific and policy projects on this subject and incited a massive literature on agglomeration economies. Many papers focus on the question whether specialised *or* diversified cities are the most fruitful environments. Duranton and Puga (2001) were the first to point out that *both* types are important in a system of cities. The question remains however how to induce such a beneficial environment and whether the advantages of proximity are similar in both city types.

A major advantage of cities seems to lay in the role of proximity for the communication of tacit knowledge and for learning from each other. Jaffe et al. (1993) show that distance bounds patent citation. Bacolod et al. (2009) and Florida et al. (2012) show that the returns to certain skills, such as social skills, increase with city size. Charlot and Duranton (2004) find positive returns to communication in French cities. This paper takes a step towards unravelling the advantages of specialised and diversified cities by analysing the role of communication in both city types. We show substantial wage returns to communication in both diversified and specialised US cities. Given their occupation, workers who communicate more are more valued by firms. These returns decrease however with the specialisation level of the urban area. Communication is positively valued in all city environments but plays more of a key role in diversified cities.

In line with the work of Duranton and Puga (2001) and Desmet and Rossi-Hansberg (2009) we relate these findings to differences in the production processes of firms across specialised and not-specialised (diversified) cities. The higher value of communication in diversified cities seems to be the result of the more crucial role of learning for firms in these cities. Specialised and diversified cities have different comparative advantages. With their location choice, firms exploit these local comparative advantages. For workers, our results suggest that social and communication skills are more valued in diversified than in specialised cities. In terms of urban policy implications, our results indicate that there is no one-policy-fits-all urban development policy as the comparative advantages vary across city types.

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Data Appendix

Data Source

Current Population Survey | May Outgoing Rotation Group

The May Outgoing Rotation Group (MORG) of the Current Population Survey is used as these files include detailed information about earnings and working hours. The files contain individual information about employment and other labour-market variables. For instance it contains information on occupation, industry, hours worked, earnings, education, unionisation and a wide variety of demographic variables. Detailed information about this dataset can be found at http://www.census.gov/cps/.

ONET Skill Survey

Detailed information about the performance of communication job tasks and other job activities is gathered from the ONET Skill Database (www.onetcenter.org). The 3.0 version is used for this paper. For each occupation this database provides information about the importance of workers abilities, interest, knowledge, skills, work activities and work context. Work activities are defined as ‘General types of job behaviours occurring on multiple jobs.’, work context as ‘Physical and social factors that influence the nature of work’. Work activities are scaled from 0 to 6 and work context from 0 to 100. To obtain similar scores, we standardized all work activities and context with mean 0 and standard deviation 1.

Local Area Unemployment Statistics

To compute employment figures for Metropolitan Statistical Areas (MSAs), we gather county employment figures from the Local Area Unemployment Statistics of the Bureau of Labor Statistics (BLS). Counties are merged into MSAs following the 1990 definition of the Census. Details on the construction of the city classifications are given below.

Classifications

Cities

Cities are classified by Metropolitan Statistical Areas in the Current Population Survey. MSAs are defined by the nature of their economic activity. The MSA classifications are updated over time following the scope of regional economic activity. We add several city characteristics to the MSA information provided by the CPS which leads to definition issues. To define time consistent MSA definitions we use the 1990 definition of the Census which combines counties into MSAs. As county borders do not change over time, our MSA classification represents cities, which do not change in geographical size over time. Thus, additional city information covers a time consistent MSA definition. This city classification leads to a sample of 168 MSAs, which borders are stable over time.

Industries

Our industry classification includes 142 three-digit and 11 two-digit industries. The distribution of industries across cities equals the County Business Patterns distribution.

Occupations

The occupational classification includes 326 three-digit and 10 two-digit occupations and follows the classification of Autor and Dorn (2010). To match information from the ONET Skill Survey to the Current Population Survey, the occupation classification from the ONET is matched to these 326 occupations. The occupation classification of ONET varies over time, the classification of ONET version 3.0 provides the most accurate match to the CPS and it used in this paper.

Variables

Table 11.10 Variables

Variables	Description	Measurement	Source
Wage	Hourly wage Note: top coded as described in Sect. 11.4	Individual level, logs	Current Population Survey 2009
Communication	Principal component index by occupation Constructed by the standardized scores of the six communication tasks as described in Sect. 11.4	Occupational level, standardized scores	ONET Skill Survey 2000
Specialisation	Regional Specialisation Index by city RSI $RSI_i = max_i \; logE_{ij} - \log E_j$ in which E_{ij} represents employment of industry j in city i and E_j the employment of industry j in national employment.	City level, standardized scores	Current Population Survey 2009
Diversity	Regional Diversity Index by city RDI $RDI_i = \frac{1}{\sum_j E_{ij}/E_j}$	City level, standardized scores	Current Population Survey 2009
Dominant industry	Dummy variable indicating whether the individual works in the dominant local industry or not The dominant industry is the industry with the highest specialisation level in the city	Individual level, dummy variable	Current Population Survey 2009

Table 11.11 Control variables

	Description	Measurement	Source
Drop-out	Dummy variables indicating whether the individual drop-out of high-school	Individual level, dummy variable	Current Population Survey 2009
High-school	Dummy variable indicating whether the highest completed education of the individual was high-school	Individual level, dummy variable	Current Population Survey 2009
Some college (College)	Dummy variable indicating whether the highest completed education of the individual was some college	Individual level, dummy variable	Current Population Survey 2009
College (College grad)	Dummy variable indicating whether the highest completed education of the individual was college	Individual level, dummy variable	Current Population Survey 2009
Communication job activities	Standardized score on the ONET variable performing for or working directly with the public’	Occupational level standardized	ONET Skill Survey 2000
Non-white	Race measurement, when the individual originates from a non-white race the dummy equals unity	Individual level, dummy variable	Current Population Survey 2009
Non-married	When the individual is not married, the dummy equals unity	Individual level, dummy variable	Current Population Survey 2009
Age and age square	Age and age squared of the individual	Individual level	Current Population Survey 2009
Female	When the individual is a female, the dummy equals unity	Individual level, dummy variable	Current Population Survey 2009
Occupation dummies	Dummy variables for each two digit occupation group	Occupational level dummy variable	Current Population Survey 2009

Table 11.12 Additional/robustness variables

	Description	Measurement	Source
Size	Employment by MSA	City level, standardized logs	Local Unemployment Figures 2009
Language-skill proxy	Average score on the following category: Who originates from a non-English speaking country? Category 1: the worker him/herself Category 2: both parents of the worker Category 3: one of the parents of the worker Category 4: nobody	Occupational level, standardized shares	Current Population Survey 2009
Population 1930	County population in 1930, summed by MSA	City level, standardized logs	Census Historical Population Figures
Relative communication	Share of communication job tasks within the total score of job tasks by occupation		ONET Skill Survey 2000
Non-routine interactive	Occupational score on the non-routine interactive job tasks as defined in Acemoglu and Autor (2011)	Occupational level, score	ONET Skill Survey 2000
Rent	Standardized average rent by MSA in 2000	City level, standardized averages	Census 2000

Table 11.13 Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
(1) Wage	1.00																			
(2) Communication	0.40	1.00																		
		(0.00)																		
(3) RSI	−0.11	−0.04	1.00																	
		(0.00)	(0.00)																	
(4) RDI	0.03	0.01	−0.45	1.00																
		(0.00)	(0.00)	(0.00)																
(5) Dom. ind	0.04	−0.03	0.00	−0.09	1.00															
		(0.00)	(0.00)	(0.53)	(0.00)															
(6) Drop-out	−0.26	−0.30	−0.00	−0.00	0.01	1.00														
		(0.00)	(0.00)	(0.68)	(0.52)	(0.00)														
(7) High-school	−0.22	−0.27	0.04	−0.01	−0.01	−0.17	1.00													
		(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)													
(8) College	−0.12	−0.01	0.06	−0.01	−0.02	−0.19	−0.38	1.00												
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)												
(9) College grad	0.46	0.42	−0.09	0.02	0.01	−0.22	−0.46	−0.49	1.00											
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)											
(10) Com. job activities	−0.09	0.32	−0.01	0.01	−0.04	−0.08	−0.08	0.05	0.08	1.00										
		(0.00)	(0.00)	(0.07)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)										
(11) Non-white	−0.07	−0.04	−0.13	−0.01	0.00	−0.02	0.02	0.01	−0.02	0.02	1.00									
		(0.00)	(0.00)	(0.00)	(0.00)	(0.41)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)									
(12) Non-married	−0.24	−0.11	−0.02	−0.01	−0.01	0.05	0.03	0.06	−0.12	0.07	0.08	1.00								
		(0.00)	(0.00)	(0.00)	(0.05)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)								
(13) Age	0.29	0.10	0.00	0.00	0.02	−0.09	0.01	−0.05	0.09	−0.10	−0.02	−0.34	1.00							
		(0.00)	(0.00)	(0.17)	(0.20)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)							
(14) Age square	0.26	0.09	0.01	0.00	0.02	−0.08	0.02	−0.04	0.07	−0.08	−0.03	−0.30	0.99	1.00						
		(0.00)	(0.00)	(0.01)	(0.36)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)						
(15) Female	−0.16	0.13	0.00	−0.00	−0.03	−0.05	−0.03	0.05	0.01	0.24	0.05	0.06	0.02	0.02	1.00					
		(0.00)	(0.00)	(0.37)	(0.78)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)					
(16) Size	0.10	0.03	−0.66	0.57	0.01	0.03	−0.04	−0.05	0.07	−0.00	0.07	0.02	−0.01	−0.01	−0.01	1.00				
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.41)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)				

(17) Proxy communication	0.27	0.67	−0.01	0.00	−0.03	−0.31	−0.16	0.06	0.26	0.27	−0.06	−0.07	0.08	0.07	0.11	−0.00	1.00				
	(0.00)	(0.00)	(0.04)	(0.23)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.74)					
(18) Population 1930	0.06	0.02	−0.51	0.61	−0.05	0.01	−0.02	−0.04	0.05	−0.01	0.03	0.00	−0.00	−0.00	−0.00	0.72	0.00	1.00			
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.33)	(0.82)	(0.47)	(0.64)	(0.00)	(0.69)				
(19) Communication share	0.11	0.52	−0.03	0.01	−0.01	−0.13	−0.07	−0.01	0.15	0.34	−0.06	−0.02	0.03	0.03	0.04	0.03	0.45	0.01	1.00		
	(0.00)	(0.00)	(0.00)	(0.06)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)			
(20) RTI	0.35	0.76	−0.02	0.00	−0.01	−0.19	−0.22	−0.07	0.38	0.13	−0.05	−0.12	0.11	0.09	0.04	0.02	0.42	0.01	0.29	1.00	
	(0.00)	(0.00)	(0.00)	(0.16)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		
(21) Rent	0.12	0.02	−0.36	0.13	0.00	0.00	−0.06	−0.03	0.08	−0.00	0.15	0.02	−0.00	−0.00	−0.01	0.27	−0.01	0.14	0.02	0.01	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.24)	(0.75)	(0.00)	(0.00)	(0.00)	(0.84)	(0.00)	(0.00)	(0.86)	(0.30)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	

Note: P-values in parentheses. See Tables 11.10–11.13 for a detailed description of the variables, measurement and data sources

Table 11.14 Correlations among communication tasks

	(1)	(2)	(3)	(4)	(5)	(6)
(1) Relations	1.000					
(2) External communication	0.800	1.000				
(3) Internal communication	0.658	0.603	1.000			
(4) Face-to-face	0.479	0.447	0.500	1.000		
(5) Teamwork	0.420	0.332	0.512	0.544	1.000	
(6) Contact	0.579	0.522	0.308	0.472	0.535	1.000

Table 11.15 PCA results for communication tasks

	Communication-indexloadings for first principal component
Relations	0.456
External communication	0.429
Internal communication	0.416
Face-to-face	0.386
Teamwork	0.371
Contact	0.386
Explained variance	0.599

Additional Figures

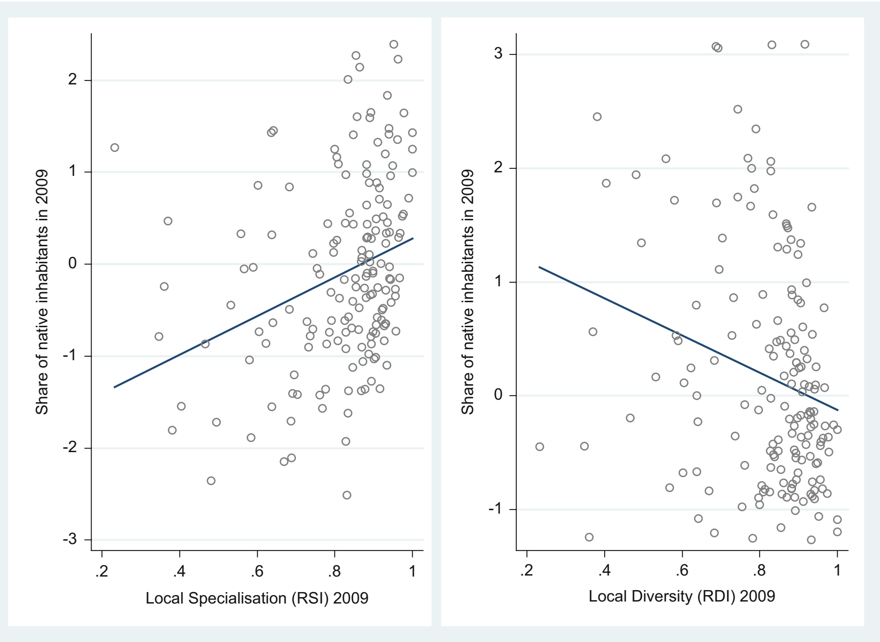

Fig. 11.4 Native inhabitants in specialised and diversified cities (Note: source Current Population Survey 2009. City level data, n = 168. The correlations are respectively 0.30 (0.00) and −0.23 (0.00) and significant at the 1 % level. *RSI* and *RDI* are measured as described in Sect. 11.3. Natives are defined as workers born in the US and are measured as share of employment)

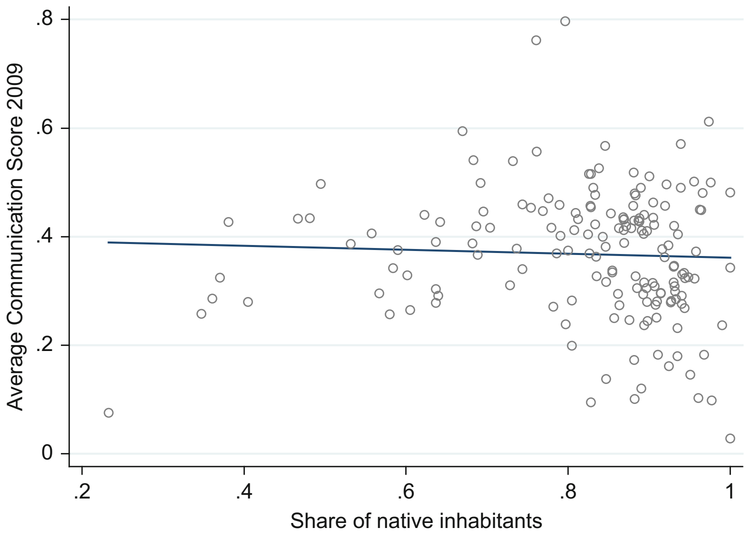

Fig. 11.5 Communication and native inhabitants (Note: source Current Population Survey 2009. City level data, n = 168. The correlation is −0.08 (0.34) and not significant. Communication is measured as the average score on the Communication-Index as defined in Sect. 11.4. Natives are defined as workers born in the US and are measured as share of employment)

References

Acemoglu D, Autor D (2011) Skills, tasks and technologies: implications for employment and earnings. In handbook for labour economics, vol Part B, 4th edn. Elsevier, Amsterdam, pp 1043–1171

Autor D, Dorn D (2010) The growth of low-skill service jobs and the polarization of the US labor market. MIT working paper

Autor D, Levy F, Murnane R (2003) The skill content of recent technological change: an empirical exploration. Q J Econ 118(4):1279–1334

Bacolod M, Blum B, Strange W (2009) Skills in the city. J Urban Econ 65(2):136–153

Borghans L, Ter Weel B, Weinberg B (2006) People people: social capital and the labor-market outcomes of underrepresented groups. NBER working paper, no 11985

Bresnahan T (1999) Computerisation and wage dispersion: an analytical reinterpretation. Econ J 109(456):390–415

Charlot S, Duranton G (2004) Communication externalities in cities. J Urban Econ 56(3):581–613

Ciccone A, Hall R (1996) Productivity and the density of economic activity. Am Econ Rev 86 (1):54–70

Combes P, Duranton G, Gobillon L (2008) Spatial wage disparities: sorting matters! J Urban Econ 63(2):723–742

Combes P, Duranton G, Gobillon L (2009) The economics of agglomeration. University of Chicago Press, Chicago/London, pp 15–65, chapter Estimating agglomeration economics with history

Desmet K, Rossi-Hansberg E (2009) Spatial growth and industrial age. J Econ Theory 144 (6):2477–2502

Duranton G, Puga D (2000) Diversity and specialisation in cities: Why, where and when does it matter? Urban Stud 37(3):533–555

Duranton G, Puga D (2001) Nursery cities: urban diversity, process innovation, and the life cycle of products. Am Econ Rev 91(5):1454–1477
Ellison G, Glaeser E (1999) The geographic concentration of industry: Does natural advantage explain agglomeration? Am Econ Rev 89(2):311–316
Feldman MP, Audretsch DB (1999) Innovation in cities: science-based diversity, specialization and localized competition. Eur Econ Rev 42(2):409–429
Florida R, Mellander C, Stolarick K, Ross A (2012) Cities, skills and wages. J Econ Geogr 12 (2):355–377
Gaspar J, Glaeser E (1998) Information technology and the future of cities. J Urban Econ 43 (1):136–156
Glaeser EL, Gottlieb JD (2009) The wealth of cities: agglomeration economies and spatial equilibrium in the United States. J Econ Literat 47(4):983–1028
Glaeser E, Maré D (2001) Cities and skills. J Labor Econ 19(2):316–342
Glaeser E, Ponzetto A (2007) Did the death of distance hurt detroit and help New York?. NBER working paper, no 13710
Glaeser E, Schienkman J, Shleifer A (1995) Economic growth in a cross-section of cities. J Monet Econ 36(1):117–143
Glaeser E, Kolko J, Saiz A (2001) Consumer city. J Econ Geogr 1(1):27–50
Harrison B, Kelley M, Gant J (1996) Specialization versus diversity in local economies: the implications for innovative private-secotr behavior. Cityscape J Polit Dev Res 54:201–242
Ioannides YM, Overman HG, Rossi-Hansberg E, Schmidheiny K (2008) The effect of information and communication technologies on urban structure. Econ Policy 23(54):201–242
Jacobs J (1969) The economy of cities. Random House, New York
Jaffe A, Trajtenberg M, Henderson R (1993) Geographic localization of knowledge spillovers as evidence by patent citations. Q J Econ 108(3):577–598
Kelley M, Helper S (1999) Firm size and capabilities, regional agglomeration, and the adoption of new technology. Econ Innov New Technol 8(2):79–103
Lemieux T (2006) Increasing residual wage inequality: Composition effects, noisy data, or rising demand for skill? Am Econ Rev 96(3):461–498
Lewis E (2011) Immigrant-native substitutability: the role of language ability. NBER working paper, no 17609
Lucas RE Jr (1988) On the mechanics of economic development. J Monet Econ 22(1):3–42
Moulton B (1990) An Illustration of a pitfall in estimating the effects of aggregate variables on micro-units. Rev Econ Stat 72(2):334–338
Mouw T, Kallenberg AL (2010) Occupations and the structure of wage inequality in the United States, 1980 to 2000s. Am Sociol Rev 75(3):402–431
Rauch J (1993) Does history matter only when it matters little? Q J Econ 108(3):843–867
Storper M, Venables A (2004) Buzz: face-to-face contact and the urban economy. J Econ Geogr 4(4):351–370

Chapter 12
Proximity Relations and Firms' Innovative Behaviours: Different Proximities in the Optics Cluster of the Greater Paris Region

André Torre and Sofiène Lourimi

12.1 Introduction

There have been some important developments in the analysis of proximity relations since its origin. First introduced by a group of French economists (Kirat and Lung 1997; Torre and Gilly 1999), during the 1990s this approach was primarily confined to the analysis of industrial production relations and was specifically developed in the context of the study of innovation processes. Industrial relations, innovation, firm mobility, new technology, territorial resources, local productive systems... all have been studied, endlessly explored and brought back under the spotlight again by the confrontation between theoretical analysis and empirical research (Boschma 2005; Carrincazeaux et al. 2008a; Rychen and Zimmermann 2008).

This analytical movement has broadened and has thematic and disciplinary extensions. However the interest in innovation processes has remained at the crux of proximity relations analysis (Baptista and Mendonça 2009; Gallie 2009). Research has focused specifically on the study of inter-firm collaborative and cooperative relations, predominantly at a local level but also between firms and their environment (Dankbaar 2007; Wetterings and Boschma 2009), under the influence of works focusing on local networks and global pipelines in the process of knowledge creation (Bathelt et al. 2004; Vaz and Nijkamp 2009). Changes in innovation and research are made from an evolutionary perspective; they are considered to be collective processes and are repositioned in their spatial and organizational context (Freel 2003; Laursen et al. 2010; Ponds et al. 2007). The

A. Torre (✉)
UMR SAD-APT, INRA, Agro Paristech, 16, rue Claude Bernard, Paris Cedex 05, F. 75231, France
e-mail: torre@agroparistech.fr

S. Lourimi
General Directorate for competitiveness, industry and services, French Ministry of Industry, Immeuble Bervil, 12, rue Villiot, Cedex 12, F. 75572 Paris, France
e-mail: slourimi@yahoo.fr

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role of geographical proximity in the spatial agglomeration of firms is highlighted (Takeda et al. 2008), as well as processes of local learning or transmission of innovation and knowledge through face to face channels (Giuliani and Bell 2005).

But, during the same period, approaches to proximity moved away from the restrictive framework of clusters and local relations to focus more on long-distance relations and their spatial connection. Proximity analyses emphasized the non-local or non-regional links of clustered firms and their crucial role in terms of innovative behaviours and competitiveness of local systems (Weterings and Ponds 2008; Biggiero and Sammarra 2010) as well as llong-distance collaboration and exchanges using ICT or mobility of engineers and researchers between professional locations or to fairs and trade shows (Bathelt and Schuldt 2010). Today, this approach also relies on the study of concepts such as Temporary Geographical Proximity or of long-distance Organized Proximity relations (Freire-Gibb and Lorentzen 2011; Torre 2008) and their influence on the behaviour of innovative firms and local organisations.

The aim of this article is to assess for the respective role of local and long-distance relations, and spatial and non-spatial proximity relations in firms innovation behaviours. We want to explore the different proximity relations maintained by innovative firms in a cluster, using an applied example. The goal is (1) to confirm the combination of internal and external links of clustered firms, (2) to clarify the respective combination or exclusion of Geographical and Organised Proximities, (3) to investigate the role played by Temporary Geographical Proximity in clustered innovation processes.

First, we shall present the different proximity relations and their connection to innovation processes by examining the two main concepts of proximity (Geographical and Organised), identifying their role within the clusters, and then reviewing the importance of Temporary Geographical Proximity relations. We shall then discuss the case study, the optics sector in the greater Paris region. We shall begin by justifying the choice of sector – representative of both innovative relations at a local level and strong external pipelines – before presenting the characteristics of the different strategic groups of firms within the cluster and the distinct relations they hold with the various proximity categories. We shall then show that the proximity approach allows for a better understanding of the network strategies and the innovation behaviours of innovative clustered firms with regards to their peculiar specificities (especially size and technological levels).

12.2 Proximity and Innovation

In this chapter, the analysis of the role and position of proximity relations in innovation processes is based on the definition of two broad categories of proximity, that we shall define as Geographical Proximity and Organized Proximity, respectively (see Torre 2008; Torre and Rallet 2005). The more or less successful conjunction or combination of the two proximity categories elucidates the relationship between firms in relation to collaboration or exchanges at a local level during research and development processes, and allows the level of interest in co-location for specific innovative activities to be measured. However, approaches in relation to Temporary Geographical Proximity should also be included in this analysis, to cater for the study of long-distance collaboration on projects and to measure the respective advantages of long-distance or local collaboration in terms of innovation flow.

12.2.1 The Notions of Proximity

A recent tradition the field of Proximity analysis identifies two main streams of research; several authors (Boschma 2005) identify four or five main types of proximities, usually quoted as geographical, social, cognitive, organisational or institutional ones. In contrast, in keeping with our previous works, we maintain the distinction between two main categories of proximity: Geographical Proximity and Organized Proximity, which encompasses various types of non-spatial proximity (Torre 2011; Torre and Rallet 2005; RERU 2008).[1] It is activation through human action that gives this potential its significance and value ("positive" or "negative") in relation to the economic and social criteria that are relevant in the societies where it is found. The activation of the proximity types gives rise to different forms of spatial relations, and especially to different types of relations and collaboration between firms, whether located within the clusters or at a distance.

The notions of proximity refer, above all, to potentialities given to individuals, groups, human actions in general, in their technical and institutional dimensions. This potential may, or may not exist at a time t, and therefore may or may not be usable or actionable through the action and representations of the actors (human or non human).

12.2.1.1 Geographical Proximity

Geographical Proximity is above all about distance. In its simplest definition, it is the number of meters or kilometres that separate two entities. But it is relative in three ways:

– In terms of the morphological characteristics of the spaces in which activities take place. There can be a « crow flies » proximity, in the case of a trip by plane for example, but the nature of the terrain also plays a role: travelling from one point to another on a flat surface is not equivalent to climbing up and down a mountain in order to go from a point A to a point B;
– In terms of the availability of transport infrastructure. The existence of a road or a highway, of a railway or metro network, of river-borne transport, will make access to a place more or less quick and more or less easy;

[1] Different notions of proximity, like relational, cognitive or institutional proximities are referred in the literature. As we will show after these notions are encapsuled in our generic two notions of geographical and organised proximities, which offer also a simplified and more straightforward framework of analysis.

– In terms of the financial resources of the individuals who use these transports infrastructures. A high speed railway line might enable people to travel more quickly to and from two places, but its cost proves prohibitive for part of the population, at least in cases when the individuals have to travel frequently. Therefore we shall say that the Geographical Proximity between two people, or between people and places, is partly related to the cost of transport, and to the financial means of individuals.

Geographical Proximity is neutral in essence. It is the way in which actors use it that matters. Thus, the fact that two firms are located in proximity of each other may or may not be a source of interaction: these two entities may remain indifferent to each other or they may choose to interact; in this latter case we talk of a mobilization of the potentialities of Geographical Proximity. But this mobilization can have different results depending on the actions undertaken. For example, in the case of innovating firms, it might be the diffusion of scientific or technological knowledge through geographical spillover effect (Bonte 2008) but it might also lead to firms spying on other firms, or unduly reaping the benefits of an invention that is supposed to be protected by intellectual property rights (Boschma 2005; Arend 2009).

12.2.1.2 Organized Proximity

Organized Proximity too is a potential that can be activated or mobilized. Organized Proximity refers to the different ways of being close to other actors, regardless of the degree of Geographical Proximity between individuals, the qualifier « organized » referring to the arranged nature of human activities (and not to the fact that one may belong to any organization in particular).[2] Organized Proximity rests on two main logics, which do not necessarily contradict each other, and which we shall call the *"logic of belonging"* and the *"logic of similarity"*. Both can help in the setting of trust relations.

The logic of belonging refers to the fact that two or several actors belong to the same relationship graph, or even to the same social network whether their relation is direct or intermediated. It can be measured in terms of degrees of connectivity, reflecting more or less high degrees of Organized Proximity and therefore a more or less great potential of interaction or common action. The development of interaction between two actors will be facilitated by their belonging to the same tennis club, or Internet knowledge network. Similarly, cooperation will, a priori, develop more easily between researchers and engineers who belong to the same firm, the same technological consortium or innovation network. It includes common organizational culture between the members of a team for example.

The logic of similarity possesses two facets. It can develop within a reciprocal relationship; a relationship which shortens the cognitive distance between the actors

[2] One may be organized or one may organize an activity without necessarily referring to or belong to an organization, in the strict sense of the term.

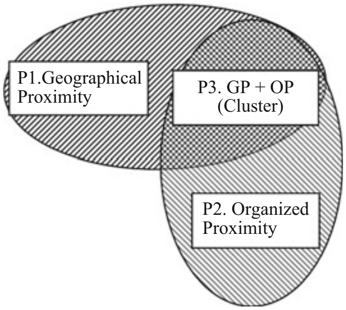
involved (common project, common education, knowledge circulating within a network. . .), but it can also emerge from a common basis, facilitating the communication between strangers (see the example of diasporas). The actors linked by a logic of similarity share certain resources, of a material (diplomas or social status) or cognitive (routines, conventions. . .) nature, which can be mobilized when the properties described here are activated.

Just like Geographical Proximity, Organized Proximity refers to a potential that is neutral in essence. It is the perceptions and actions of individuals that give it a more or less positive or negative dimension, and therefore a certain usefulness. Thus, being connected by a logic of belonging is not a guarantee that interactions will occur, and even less a guarantee of the quality of these interactions. It is human actions that determine whether or not actors are going to start interacting, just like the circulation of electricity through a wire. And results of the interactions vary in this regard: a firm may enter into a relationship with a laboratory in order to collaborate with the latter, or rather to try and rob the laboratory of one of its inventions. For the logic of similarity, the power already exists but it needs connection. With regards to the results of interaction, a common project has as much chance to lead to an industrial or technological success as to end up in a failure resulting in heavy losses for the parties involved.

12.2.2 The Role Played by Proximity Within Clusters

Several applied works have been devoted to the study of proximity relations within clusters (see Biggiero and Sammarra 2010; Carrincazeaux et al. 2008b; Takeda et al. 2008; Weterings and Ponds 2008). Following on from the definition of the notions of proximity, we shall proceed to analyse the interaction of the different Proximity types and explore further the manner in which they contribute to relations between economic and social actors. The combination of Geographical and Organized Proximity provides some understanding of the coordination and communication process between actors, both local and remote, based on the following hypotheses:

- *P1. The potential of Geographical Proximity can remain inactive, or not mobilized*. Two people or two firms can find themselves in a situation of Geographical Proximity without interacting with one another. A laboratory can be located in Proximity to a firm with which it has no connection.
- *P2. The potential of Organized Proximity can remain inactive*. This is the case for people of the same geographical origin or who come from very similar cultures but who do not meet or communicate with one another. Organized Proximity remains a potential state and is only activated by the establishment of interaction based on the actions of groups of individuals or institutions.
- *P3. The simultaneous mobilization of the two types of Proximity gives rise to situations of localized coordination*. This is the case of "working" clusters, local innovation networks or family gatherings, situations where the combination of



The combination of both types of Proximity corresponds to a situation where the Potential of Geographical Proximity is permanently activated through interaction with Organized Proximity. This situation is particularly significant for clusters or local production and innovation systems (of which schools are often cited as an example), which are one of the combinations in the articulation of the two broad categories of Proximity. It should be noted that this combination is difficult to achieve as it requires the co-location of the actors involved, the mobilization of which often depends on the existence of appropriate policies.

Fig. 12.1 The articulation of the two major categories of proximity within a cluster

Geographical and Organized Proximity promotes the establishment of coordination and interaction processes taking place in a specific location.

It is possible to infer that the two categories of Proximity (Geographical and Organized Proximity) can either evolve separately or together, as shown in Fig. 12.1.

The combination of both types of Proximity corresponds to a situation where the Potential of Geographical Proximity is permanently activated through interaction with Organized Proximity. This situation is particularly significant for clusters or local production and innovation systems (of which schools are often cited as an example), which are one of the combinations in the articulation of the two broad categories of Proximity. It should be noted that this combination is difficult to achieve as it requires the co-location of the actors involved, the mobilization of which often depends on the existence of appropriate policies.

The intersection of the two categories of proximity provides an analysis framework for the different models of geographical organization of activities. In the "winning" clusters, not only are the firms located in the same place (Geographical Proximity) but they also are closely linked and maintain privileged relationships with one another (Organized Proximity), in terms of the technology exchange and knowledge transfer. This is the ideal situation, one which every local decision-maker dreams of creating within their sphere of influence.

Although widely discussed in economic literature, this model is only one possibility among others in the interaction of proximity types, and is not that commonly observed in reality. Indeed, Organized Proximity – consisting of functional relations (interaction) or relations between people sharing the same identity (common beliefs and cognitive maps) based on organization rather than territory – often exists independently of Geographical Proximity. Similarly, firms may find themselves in Geographical Proximity of one another without maintaining any organized relations. In this situation Geographical is permanent in nature. Firms or laboratories are located on the same site and therefore at short distances from one another. Furthermore, these entities have formed relations of Organized Proximity, such as client-supplier relationships, exchanges of know-how or various kinds of cooperation.

This alchemy, albeit exceptional, is based on the activation of Geographical Proximity by organizational and institutional actions. In other words, in order to reveal the full potential of Geographical Proximity, it is necessary to mobilize the logic of belonging or the logic of similarity of Organized Proximity:

– From an organizational point of view, this requires collective action at a local level, and more importantly the establishment of common projects. These projects may consist of collaboration between different firms or laboratories for the co-development of products or for the provision of technical support or mutual assistance within the same group; or also of cooperation projects jointly undertaken by firms or research laboratories. Local skills and knowledge are combined to work towards a common goal shared by a group of co-located participants. It is in this context that the potential benefits of Geographical Proximity can be realized and contribute to the creation of synergy within the local system;
– But the institutional dimension and the role played by history and time in the mobilization of the potential benefits of Geographical Proximity must not be underestimated. Just as the examples of the Hshinsu Technopole in Taiwan or Sophia Antipolis (Lazaric et al. 2008) have shown, the creation of synergy within a local system is based on the development of shared representations or expectations by local actors: it can be said that Geographical Proximity is activated by the mobilization of the logic of similarity associated with Organized Proximity. Furthermore, time favours the creation of a local innovation network and the transition from the juxtaposition of R&D activities to a system characterized by organized relations, by the creation of a sense of belonging and common representations, through successive confidence-producing interactions.

12.2.3 Introducing Temporary Geographical Proximity

Taking into account long-distance relations rests on the explicit integration of the processes of mobility and ubiquity of actors. The multiplication and ever-increasing technological level of land and aerial transport infrastructures, has now combined with the revolution of ICT. All have led to significant modifications in actors' relations to space and to the development of new relations between economic and social actors (Torre and Rallet 2005).

12.2.3.1 Mobility and Ubiquity Condition Long-Distance Relations

The phenomenon of mobility is related to Geographical Proximity. The increasing mobility of people enables individuals to act in different places, at different, but often close, moments in time. It can be long-term mobility, when people move homes for example, or when a firm relocates to new premises; it can be « short term » or Temporary in the case of people going on holiday, or on work-related trips; or it can be « pendular » for example in the case of individuals who need to travel everyday in order to go to various distant work places.

These types of mobility have developed dramatically. This evolution is possible thanks to the development, and above all, the technological improvement of transport technologies: Increasing frequency of flights, increasing number of high speed trains or of highways for example, or the shortening of the time needed to go from one point to another (particularly in the case of the railway).

Transport infrastructure and technologies help to reduce access times or draw individuals closer to places or objects they are interested in, thanks to the multiplication of connections and to the increase in travelling speeds. They promote and facilitate interactions between people, helping them to develop maintain or re-activate relationships. They are at the heart of temporary meetings, which are characterised by a temporary and simultaneous activation of geographical and Organized Proximity by enabling actors located far from one another to meet face-to-face.

Thanks to the development of ICT, actors or groups of actors now have the ability to be at once here and there and therefore to perform a range of actions that transcend location or mobility. Any actor cannot only be at once mobile and physically present in one place, but it can also act in real time in different places. An individual can interact by telephone or through the Internet with people who live in other countries or regions. A firm can act at once locally and globally, for example by making its suppliers compete with each other at global level, or by passing orders on stock exchanges abroad. ICT multiply the possibilities of interactions. Following social psychologists (Walther et al. 2005) computer-mediated interactions mobilize an important part of the cognitive and emotional capacities of individuals and contribute to the creation of new social relations.

Their evolution has above all had an impact on Organized Proximity, in its potential dimensions as well as in its activations. Indeed, ICT are closely related to the logic of belonging and the logic of similarity in that they contribute to the creation of connections and networks between human beings. Furthermore, they enable individuals who are separated by large geographical distances but short cognitive distances to enter into interaction with one another, which used to be difficult in the past. ICT facilitate the creation of relationships between people located geographically far from one another, or between people who have never met.

12.2.3.2 Temporary Geographical Proximity

In order to account for these processes, let us introduce the notion of Temporary Geographical Proximity (TGP) (Torre and Rallet 2005). The development of communication technologies and ICT facilitates long-distance exchange; consequently co-location no longer constitutes an absolute necessity. A large part of the information and knowledge that are necessary for production or innovation activities can be transferred from a distance, through telephone or Internet mediated exchanges for example (Walther et al. 2005). However, times of face-to-face interaction are necessary and beneficial in this context. The example of the Airbus or Renault platform teams, or that of the travelling done by members of R&D (Research and Development) collaboration projects undertaken by biotech start-ups are good examples of such situations. Face-to-face interaction cannot altogether be eliminated, including in the case of communities of practice, for example (See Torre 2008). As a consequence ICT cannot be considered as substitutes of face to face relations: they are useful tools to support or enhance the interaction between two or several individuals.

Space matters, but in a new way; one that consists of Temporary face-to-face contact between two or several individuals. Temporary Geographical Proximity corresponds to the possibility of satisfying *needs for face-to-face contact between actors, by travelling to different locations. This travelling generates opportunities for moments of Geographical Proximity, which vary in duration, but which are always limited in time.*[3] *TGP is limited to certain times; this form of Geographical Proximity should not be mistaken for a permanent co-location of firms or laboratories.*

The necessity of TGP is embodied in the existence of places that are especially made for TGP based activities. In the case of private individuals they can be conferences, theme or recreational parks. In the case of firms or laboratories they are specialized venues. Trade shows, conferences and exhibitions enable actors to fulfil certain needs related to the processes of production, research or innovation (Entwistle and Rocamora 2006). These hubs are readily viewed as Temporary clusters (Maskell et al. 2006), a term which highlights the relation with the permanent clusters. But above all, these places respond to a need for face-to-face relations related to the wish to reduce the costs of transactions (Norcliffe and Rendace 2003; North 1991). Common "platforms" of project teams are also meant to enable the participants of a project to work together for a period of up to several months, in the framework of a project team. It is also the case of the members of a project undertaken by the geographically dispersed subsidiaries of a firm (Aggeri and Segrestin 2001; Kechidi and Talbot 2010).

[3] The type of mobility we are discussing here is a "long" mobility, one that is not "pendular", for example. It consists of time consuming trips with high transport costs. "Short" mobility, within a local system shall be considered, in a conventional manner, as permanent proximity or co-location.

Business trips are undertaken in order to reach a common decision or determine the characteristics of a cooperation project; or an activity that can only be performed in a place other than the individual's usual workplace. These meetings are needed at regular intervals during the coordination process. Their frequency and regularity are the cause of most business trips. The face-to-face interactions do not, in this case, occur in places exclusively dedicated to meetings, but in "ordinary" places, i.e. in the participants' usual workplaces, firms or laboratories.

12.3 Assessing Proximity Relations and Innovation Within the Optics Cluster in the Greater Paris Region

Let us proceed to apply our analytical framework to the study of inter-firm relations. The objective is to understand the role played by the different types of proximity (internal vs external, geographical vs organised, and permanent vs temporary) within innovative firms strategies and behaviours and to understand the balance between local and long-distance relations in the field of clustered innovation activities.

It has been recently showed that innovative firms can have specific behaviours in terms of proximity relations, with regards to their own peculiarities (Dankbaar 2007; Weterings and Boschma 2009). We want to investigate this field, with a more precise assumption. Regarding our previous developments, we would like to confirm the intuition that large firms will be more easily able to act at a global scale, with the help of Temporary Geographical Proximity and Organised Proximity relations, whereas smaller ones are more anchored and constrained to stronger local links. This is due to the ability of large organisations to take advantage of travels and mobility due to their financial and human resources. This hypothesis is not an obvious one: one could make the assumption that smaller firms are easily footloose because of a small number of employees, tiny links with local employment markets and unweight fixed capital, especially in innovative sectors based, whereas large firms are spatially anchored due to huge local investments in human or fixed capital.

For the sake of this analysis, our case study must correspond to several conditions:

– We need a well-defined geographical concentration of innovative firms, with attested internal relations and global pipelines;
– We are looking for a diversified population of local firms, with small and big firms, and SMEs, and various technological levels, in order to assess for possible different innovation behaviours related to peculiar situations and competitive positions.

In order to obtain all the necessary information to complete this task, we have focused on a sample of firms displaying the following two characteristics:

– Firms belonging to a cluster with a manifest institutional presence, which guarantees the presence of local relations and synergy, without excluding external relations to the cluster;

– Firms engaged in processes of production and distribution of innovative products that are sufficiently complex to require the involvement of a number of actors, in other words the activity cannot be carried out by a single entity.

12.3.1 The Selection of the Optics and Photonics Industry and the Method of Analysis

12.3.1.1 The Choice of Case Study

We chose to study firms that develop optical and photonic technology, based in the greater Paris region. This selection was made for four reasons. (1) This cluster has well-defined geographical and institutional boundaries; (2) It encompasses a huge diversity of types of firms, large, small and medium-sized ones, (3) There are important differences in terms of technological levels, from lower medium to upper high tech; (4) There are confirmed internal relations between these firms, as well as strong external links and remote relations.

The greater Paris region has a large agglomeration of actors from French subsidiaries involved in the optics and photonics industry: about half of the French-based industry and research entities in optics and photonics can be found in this location,[4] namely approximately 556 firms with more than 16,700 employees and 103 public research teams (more than 5,000 employees), thus forming a very large cluster dedicated to these activities. In addition to this significant presence, a high concentration of research activity in various optics-related fields is carried out in major university centres within the region. The area also brings together more than half of the national research entities in the field of optics as well as large scientific facilities.

Optical and photonic technology is characterized by a strong level of technological innovation, it is multi-applicative and supplies all the major strategic industrial sectors. The industry develops critical technology (*enabling technology* and *constitutive technology*; ISTAG 2006) that, when combined with the electronics and software industries, enables the creation of finished products (calculators, endoscopes, film cameras, RFID, CAD, telecommunication networks). This combination with other technologies – especially electronics, signal processing, or mechanics – allows advances to be made in relation to the integration of advanced functionality within sensors or optical equipment, thus opening out the field to new uses such as pollution control, non-destructive analysis and control, image

[4] This significant base in the greater Paris region is characterized by the establishment in 1999 of a structure to lead and promote the optics and photonics sector, *Opticsvalley* (http://www.opticsvalley.org/). Since 2005, *Opticsvalley* has also included branches of software engineering and electronics.

recognition, holographic control procedures... Optical equipment and instruments – which are sometimes in competition with other technological solutions (for example, water jet or plasma for cutting) – are the focus of research that aims to address certain weaknesses such as environmental protection or high production costs (Opticsvalley 2004). The main markets for firms within the optics and photonics industry are ICT (optical and photonic components), the aerospace and arms industries, health and life sciences, scientific instruments, industrial production and other markets (LED sources with higher light output than traditional incandescent lamps).

The relevant actors for this study were identified using data and knowledge bases developed by the economic development organization *Opticsvalley* and the global competitiveness cluster *System@tic-Paris-Région*, encompassing over 1,100 firms in the greater Paris region that carry out production and/or development activities in the optics, electronics and software industries. Of these entities, there are:

- 42 large entities (greater than 100 employees) with over 8,500 employees,
- 77 medium entities (between 20 and 99 employees) with over 4,600 employees,
- 437 small entities (fewer than 20 employees) with over 3,500 employees.

In order to study the characteristics of the optics sector and the interrelations in terms of proximity, we have used two main sources. The first is a database in which all firms based in the greater Paris region (123 firms[5]) that develop and/or produce optical and photonic technology are identified and classified in terms of number of employees, turnover, location, focus on R&D, technology and products developed. The second is the output of 44 qualitative in-depth interviews conducted with the most representative local actors in the industry[6] (industry, research, institutions).

12.3.1.2 The Method

A part of our method is based on the idea that firms could exhibit various strategies with regard to different types of proximity, related to their own peculiarities or competitive positions. For commodity sake, we use the porterian approach of strategic groups, in order to identify different groups of firms, with peculiar behaviours and industrial or innovative dimensions.

In order to identify and classify the main categories of innovative firms, we have used the industry structural analysis method[7] based on tools developed by industrial economics, which aims to study firms by placing them in their industrial context.

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[5] See Annex 2.

[6] 21 industrial firms, 6 economic development organizations, 5 local authorities, 3 financial institutions and 9 public research laboratories.

[7] The changes in the global economy and the new strategies developed by firms can be analysed by this method, using the basic factors that determine the evolution of an industry (intensity of competition, substitute products, presence of suppliers, customers and new entrants).

Industry is defined as a group of firms producing goods that are highly substitutable. The analysis of the immediate competitive environment of firms (i.e. other firms within the same industry) is completed with the analysis of the set of forces external to the industry that affect its competitiveness. Porter (1980, 1998) defines customers, suppliers, substitutes and potential entrants as competitors of greater or lesser importance. He has defined this form of competition as *extended rivalry*. Consideration of the five competitive forces – (1) the potential entry of new competitors, (2) the possibility of product substitution, (3) customer bargaining power, (4) supplier bargaining power and (5) competitive rivalry – shows that competition within an industry far exceeds the competition between established firms in the market and requires a broader view of the environment in which they operate. The overall impact of these five forces determines the profitability of firms within an industry, however it should be noted that this impact varies by industry and can evolve over time.

1. *The potential entry of new competitors*

   New entrants to an industry can increase overall production capacity, however they also aspire to take market share and can aim to appropriate part of the existing resources. Acquisitions within an industry, coupled with a desire to increase market share, should be analysed as a new entrant even if no new entity is created. Porter's analysis framework highlights the need to consider barriers to entry for the industry under review, working from seven major sources: economies of scale, the degree of product differentiation, the level of risk associated with the capital investment by the firm, switching costs, access to distribution channels, cost advantages independent of scale and the level of state intervention. The likelihood of new entrants to an industry is therefore dependent on the level of barriers to entry and the opinion of new entrants on how existing firms within the industry will react (*expected retaliation*). Indeed, if the barriers to entry are high and/or if the new entrant expects a strong reaction from firms already established in the market, the likelihood of new competitors entering the market is low.
2. *The intensity of competition*

   Existing firms within an industry are mutually dependent in the sense that action from one firm (i.e. price decrease, product enhancement) may result in a reaction from its competitors. The intensity of competition between firms within an industry depends on several structural factors that interact with one another. These factors are: the existence of many similar-sized competitors; a low-growth industry, which pushes competitors to develop acquisition strategies in order to increase their market share; high fixed prices or storage costs, which often prompt a strategy of price reduction when there is production overcapacity in the industry; low levels of product differentiation; a significant increase in production capacity; competitors with a wide variety of different strategies, originating within the firm, from personalities...; and significant switching costs (asset specificity, strategic interactions, high fixed switching costs, emotional barriers, state or social restrictions).

3. *The pressure of substitute products*

   One product can be substituted for another if they both perform the same function. The choice between two substitutable products is based on the price/performance ratio of each product. Product substitutes are not part of the market, but they represent an alternative to those on offer. They could be different products that meet the same need (e.g. MP3 downloads/Compact Discs), or products that influence demand (electric vehicles/fossil fuels).
4. *Customer bargaining power*

   Customers can exert pressure by asking for price decreases, better quality products, more services, thus promoting competition within the industry. The bargaining power of each buyer group[8] is strong when:

   - There are few buyers, or the customer purchases large volumes of production output,
   - The products purchased represent a significant portion of the total cost or total purchased,
   - The products purchased are standardized, or not differentiated,
   - The supplier switching cost is low,
   - The buyers have a low profit rate,
   - The buyers are potential entrants to the industry,
   - The products purchased have a low impact on the quality of the buyer's end product,
   - The buyer has complete information on market demand, market prices and production costs.

5. *The bargaining power of suppliers*

   Suppliers can exercise their bargaining power by threatening to increase prices or reduce the quality of the products and services supplied. The bargaining power of a supplier group is strong if it is dominated by a few firms and is more concentrated than the industry it sells to, if there is no competition from product substitutes, if supplier products constitute a large portion of the buyer's end product, if the products are differentiated, if supplier switching costs are significant, and finally, if the suppliers are potential entrants to the industry of the customer.

This model has some limitations: it is based on the logic of power in relationships and leaves little room for collaboration strategies which have recently acquired a new legitimacy as a result of the globalization of economies, coupled with increased complexity and uncertainty in technological developments and the markets, not to mention the financial dimension. For this reason, we have included these collaborative relations in our study. In addition, the model implies that the strategy is essentially to adapt to environmental conditions, thus

[8] One buyer group represents all firms that buy a given product. The firms are not necessarily part of a formal organization with a legal status.

precluding approaches based on resources and skills that foster an endogenous vision of success. Finally, the model can be extended by the addition of a sixth force – the influence of public authorities (State, European Commission, local authorities, etc.) – which does not explicitly feature in the model but whose influence can affect each of the five other forces. The implementation of policies and legislation can affect the manner in which each of the forces impact the market. For example, market entry may be subject to approval or, conversely, it may be subsidized.

12.3.2 The Characteristics of the Different "Strategic Groups" of Firms Within the Optics and Photonics Industry in the Greater Paris Region

The application of the structural analysis method has led us to identify four strategic groups of firms within the optics and photonics industry located in the greater Paris region. Each group is categorized by similarities in strategies adopted, mobility barriers from one industry to another, the level of bargaining power with customers and suppliers and in their position in relation to substitute products. The categorization of these strategic groups does not preclude interdependence between the respective markets (see Fig. 12.2).

12.3.2.1 "Breakthrough Technology" Start-Ups

Firms in the "breakthrough technology" start-up group are characterized by their ambition to introduce new technology products to the market. Solutions developed using recent knowledge do not necessarily have an identified market and the innovation does not stem from a specific or existing need, this phenomenon is known as technology push. This category of firm is identified mainly by the small number of employees (between 1 and 20 in the majority of cases).

Research carried out in large public or private laboratories is the main source of this new knowledge. These laboratories are at the forefront in their respective technology fields and are therefore likely to transform their research and development activities into products, either by knowledge transfer to the industry or through spin-offs. Mastering new technologies introduced by start-ups is the main mobility barrier in this strategic group. They introduce new technology products which are likely to become substitutes for established products in the market. The degree of market penetration depends mainly on the price/performance ratio of the new technology and its ability to establish a new standard in the market.

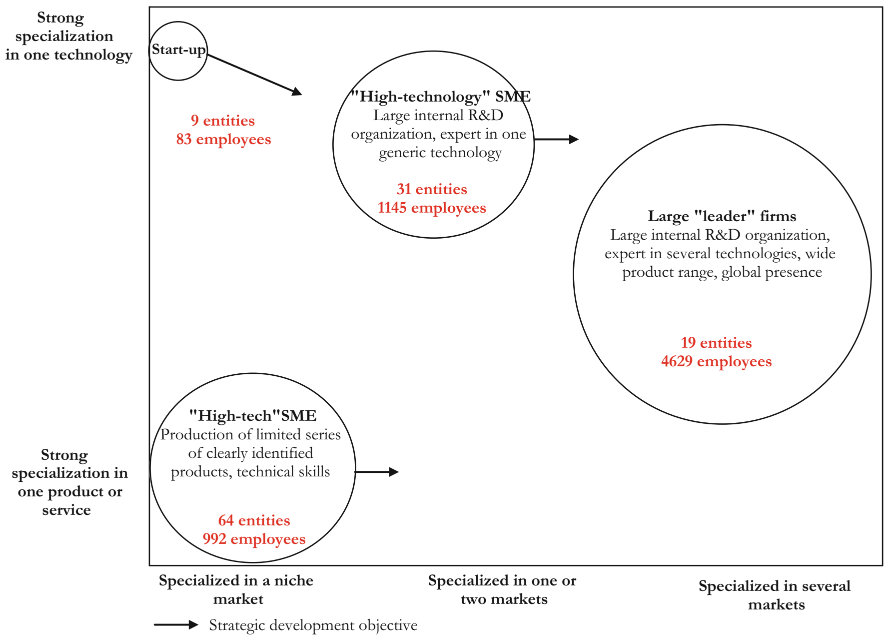

Fig. 12.2 The "strategic groups" of firms of the optics and photonics industry

12.3.2.2 "High Technology" SMEs

"High technology" SMEs are characterized by a large internal R&D organization, enabling them to develop and introduce numerous innovative products to the market at regular intervals. They are identified mainly by their specialization in one generic technology (infrared, lasers. . .) from which they develop a wide range of products aimed at several markets (health, automotive, aeronautics, environment, defence, telecommunications. . .).

The significant technological expertise and knowledge acquired by these firms are strong mobility barriers in this strategic group. "High-technology" SMEs have low bargaining power with their customers, with the exception of product co-development initiatives. This is mainly because the customer (often a large firm) is looking for a specific recognized skill that does not exist internally and that can be provided by the SME. On the other hand, the bargaining power of the SMEs generally works in their favour with "standard" suppliers (who sell intermediate products that are in abundance on the market), but is low with "strategic" suppliers (who sell very specific intermediate products that are rare on the market). Finally, the generic nature of the technology used means that the firms are faced with the constant threat of substitute products using other technologies, which can be evaluated using the price/performance ratio (optics, photonics, electronics, electromagnetic. . .).

12.3.2.3 "High-Technicality" SMEs

"High-technicality" SMEs are characterized by a significant level of technical specialization and by the production of limited series and customized products for clearly identified market niches. In addition to a low focus on R&D, the main difference with "high-technology" SMEs is the fact that while "high-technology" SMEs are experts in one generic technology (which is possibly applicable to several markets), "high-technicality" SMEs are characterized by their strong specialization in one product or service destined for a specific and clearly identified niche market.

This strong specialization in a product/service, coupled with a specific distribution channel, are the main mobility barriers in this strategic group. These firms have low bargaining power with their customers (large firms, large research laboratories) to whom they supply small quantities of products that are generally not very strategic in nature. However they have a strong bargaining power with their suppliers, because many firms are able to supply the production inputs, including firms based in emerging countries. There are no immediate threats identified in relation to substitute products, this can be explained by the small market size which is not very attractive for potential competitors. However, this strategic group is at risk of the emergence of a new substitute technology with a better price-performance ratio.

12.3.2.4 Large "Leader" Firms

The greater Paris region has a significant presence of large multinational industrial groups that develop, produce and integrate optical and photonic technology. Among these are Alcatel, EADS, Safran, Thales and Tyco Electronics, each with greater than 60,000 employees world-wide.

These firms have market relationships that are similar to those of other groups. But their relations with the state, technology and the territory are different to those of SMEs. Indeed, the state may be a shareholder or the only customer of large firms, in certain strategic markets such as nuclear and defence, for example. Unlike SMEs, who often produce technological components (lasers, infrared...), the large "leader" firms play a dual role as producers of certain technological components for their core business, but primarily as integrators and manufacturers of complex systems. They play a major role in the definition of technological standards and products destined for the market and have a balanced bargaining power (sometimes strong when they have the monopoly on a product or service) with their customers (the state or private markets) and a very strong bargaining power with their suppliers. The threat of substitute products is quite weak in the short and medium term, especially as large firms have the financial capacity to acquire competitors who develop products and processes based on a radically innovative technology.

Finally, their relationship with territory is characterized by the international organization of their R&D and production activities. They play a leading role in the general economy by buying products from suppliers, co-developing technologies with SMEs or laboratories and identifying actual and future consumer preferences in terms of products and services.

12.3.3 The Proximity Relations of Firms Within the Strategic Groups

Taking the main elements of our working method and the typologies detailed above, we can draw a graph of the different types of relations between the firms in the Paris region optics sector, belonging to the four strategic groups (Fig. 12.3). This diagram, based on the existence of "standard" and "strategic" customers and suppliers, as well as partner firms and laboratories, also includes the role played by institutions such as public bodies. Customer/supplier relationships are part of the value chain and can foster major product development and enhancement activities, while partnerships with other companies or laboratories have more horizontal relationships.

In our case study, the innovative firms maintain three types of proximity relations with their partners. Relations can be:

- Permanent Geographical Proximity relations, activated by Organized Proximity relations and which are based on local interaction through meetings or more informal encounters (face to face). To a greater or lesser extent, these relations may be accompanied by;
- Temporary Geographical Proximity relations, which also rely on Organized Proximity relations and involve the organization of short visits and trips using different means of transport (mobility);
- Long-distance Organized Proximity relations that depend on the use of ICT, such as the telephone or internet.

This diagram characterizes the relations between firms and their local or wider environment in terms of Geographical and Organized Proximity as well as in terms of internal or external links to the cluster. It is only a general and broad image, which does not take into consideration the peculiarities of various groups of firms. In the following diagrams, we try to clarify the respective combination or exclusion of geographical and organised proximity, and we describe the complete set of proximity interactions of firms, while at the same time focusing on the analysis of research and innovation partnerships. We made the choice, for sake of completeness, to maintain other relations than innovation ones in the graphs, but they are depicted in grey (relations with suppliers or standard customers, for example).

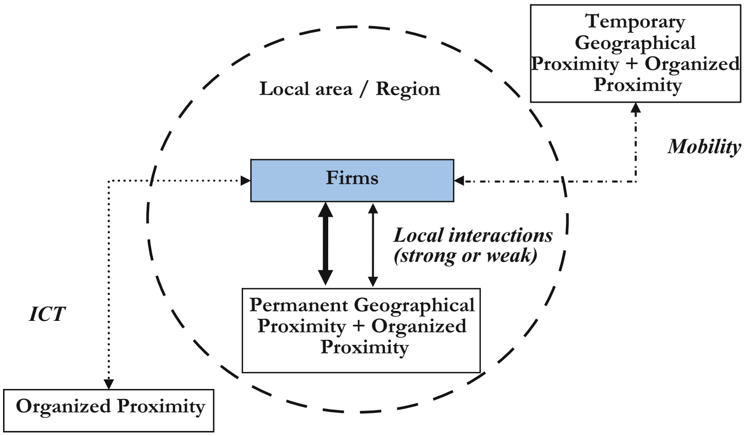

Fig. 12.3 The proximity relations of firms within the strategic groups

12.3.3.1 The Importance of Permanent Geographical Proximity Between "Breakthrough Technology" Start-Ups and Public Research Laboratories

The main characteristic of "breakthrough technology" start-ups is to attempt to introduce products using new technology to the market. They do not yet have catalogue products and their products are in an operationalization phase, characterized mainly by numerous interactions, especially significant exchanges of knowledge and information with research laboratories and large companies that can be defined as *early users*. These *early users* are the first customers, they identify the new product or service and pinpoint a significant potential application for it within their own production processes or products. *Early users* are: public institutions (national and/or regional) that decide to purchase products or services utilizing this new technology, or public laboratories, that can also be a potential market for these start-ups. They provide initial feedback to the start-up on the feasibility of and interest in their product. This valuable source of information strengthens the ability of start-ups to issue competitive products and services to the market (Fig. 12.4).

In our cluster, "Breakthrough technology" start-ups have a fundamental requirement for permanent Geographical Proximity with research laboratories (especially with laboratories from where the start-ups originated, which creates a sense of belonging in terms of Organized Proximity). They require access to the skills and tools/infrastructures available in nearby laboratories in order to test and develop their products. The role Geographical Proximity plays is particularly central in allowing start-ups to execute their innovation processes in the product operationalization phase, they are very closely linked to the research laboratories within their local environment, especially with their laboratory of origin. Indeed, the use of skills and tools/infrastructures, which are too costly for a young firm to

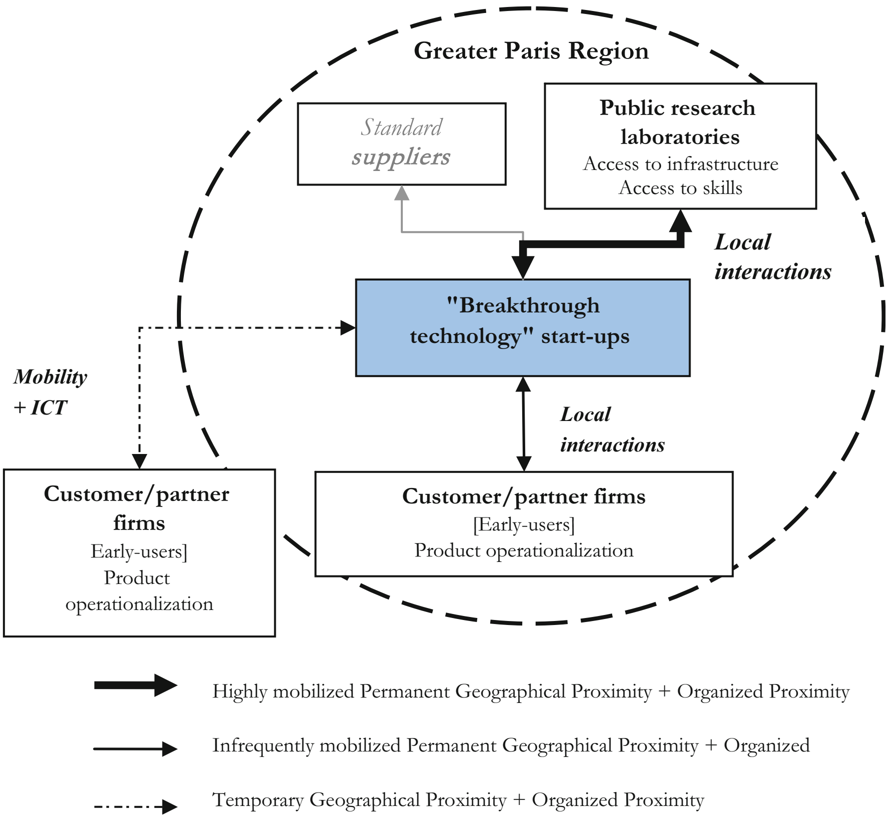

Fig. 12.4 The proximity relations of "breakthrough technology" start-ups

acquire, are critical and a determining factor in the ability of the start-up to solve technical and scientific problems and propose an end product. These exchanges are difficult to perform at a distance as they require a frequent repetition and mobilize tacit dimensions. Thus, research laboratories are often a source of materials (test and measurement tools, for example) and skills (access to the research skills) for breakthrough technology start-ups, in addition to the existing resources within the firm itself. This relationship is essential for firms with limited financial and human resources (i.e. insufficient turnover to guarantee the immediate survival of the firm) which restricts their capacity to acquire materials in order to develop new products or services and which anchors them firmly at a local level.

Furthermore, Geographical Proximity plays a greater or lesser role according to the relations between *start-ups* and other firms:

- Permanent Geographical Proximity with *early user* customers is not a prerequisite for effective interaction in the product operationalization phase. Start-ups interact with firms (in general with large groups of firms) that are interested in their technology, regardless of location. The product operationalization phase requires "instant" interaction with a view to adapting the products to specific customer needs and effectively assessing the potential of the new technology in relation to their products or processes. An indispensable factor in this operationalization phase, Temporary Geographical Proximity is mobilized by partners located at a distance from one another, and Permanent Geographical Proximity is infrequently mobilized by relations with partners within the cluster.

- Geographical Proximity is incidental in the interaction between "breakthrough technology" *start-ups* and "standard" suppliers, whether located in the same region or elsewhere, and without the interactions having to be especially strong. Although the purchase of intermediate goods does not require face-to-face contact, it is often carried out locally, especially in the case of economic areas with a large and diversified industrial fabric. The firms purchase their inputs locally if they are satisfactory from a quality/price perspective. This results in occasional relations with other partners in the cluster. The potential of Permanent Geographical Proximity is infrequently mobilized and local relationships are not vectors of knowledge or skills transfer for this category of local interaction, which is easily replaced by supra-local interaction.

12.3.3.2 The Key Role of Temporary Geographical Proximity in Relation to "High-Technology" SMEs

"High-technology" SMEs are characterized mainly by a strong internal R&D organization, required in order to maintain their competitiveness in the global market. These firms need to introduce successive series of products to the market at regular intervals. These characteristics, which push them to establish interaction with other firms and public laboratories, result in very different requirements in relation to Geographical Proximity, depending on their partners.

Geographical Proximity plays a central role in the interactions between these firms and their customers/partners. Temporary Geographical Proximity relations with customers/partners situated outside the region are mobilized using ICT during phases of long-distance collaboration. Indeed, "high-technology" SMEs – whose goal is to adapt highly technological products to the new needs of a customer (generally large companies) – have many face-to-face interactions, especially during the requirements gathering phase in which the SME ascertains the customers' needs and the customer evaluates the ability of the SME to supply a complementary technology. Not only does Temporary Geographical Proximity play a fundamental role in these preliminary phases, it is also a key element in the intermediary phases of product co-development and adaptation to the customer's specific needs: Temporary Geographical Proximity manifests itself in the form of meetings to evaluate progress on cooperation projects. Co-location is not necessarily a prerequisite for these temporary meetings to take place: co-location with local customers is more the result of the history of the region and the search for skilled labour.

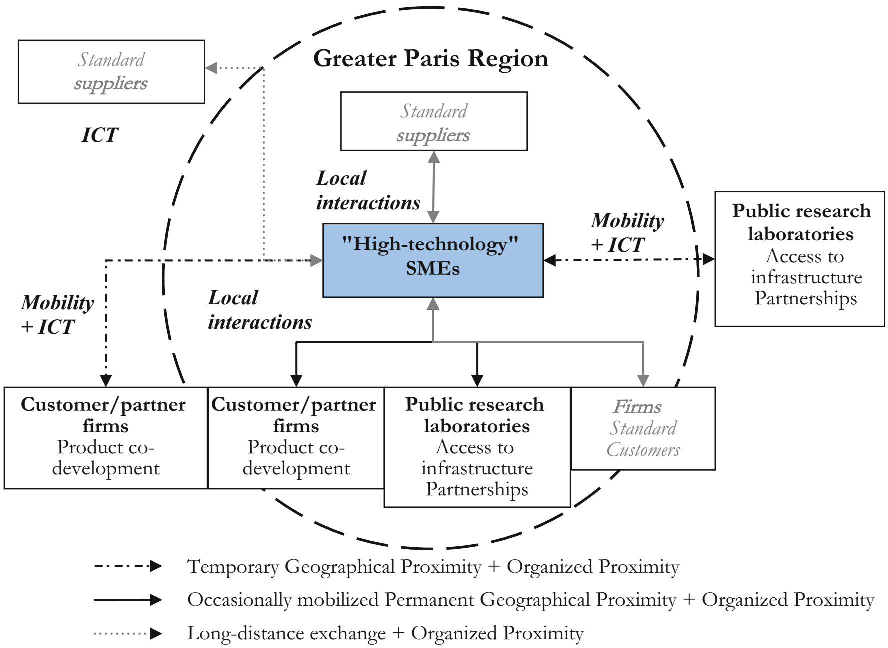

Fig. 12.5 The proximity relations of "high-technology" SMEs

Interactions between "high-technology" SMEs and research laboratories also require regular meetings, especially in the initial and control phases of collaborative R&D projects when frequent face-to-face meetings take place. Direct contact is also indispensable if the firm wishes to access the infrastructure and/or skills available in public research laboratories. These relations are all the more important as the actors behave in different ways, according to different logic. Similar to partner firms, there are two different types of mobilized Geographical Proximity for "high-technology" SME/laboratory relations: it is temporary for laboratories located outside the region, and permanent for laboratories co-located within the greater Paris region. In both cases, mobilization is only occasional (Fig. 12.5).

12.3.3.3 The Accessory Role of Permanent Geographical Proximity in Relation to "High-Technicality" SMEs

Our "High-technicality" SMEs are characterized by a high level of technical specialization, by the production of limited series and custom-made products for clearly identified markets. Products produced by firms in this category have technical characteristics that are known and mastered by customers and leave little room for interactive innovation with other firms. The main elements of the incremental

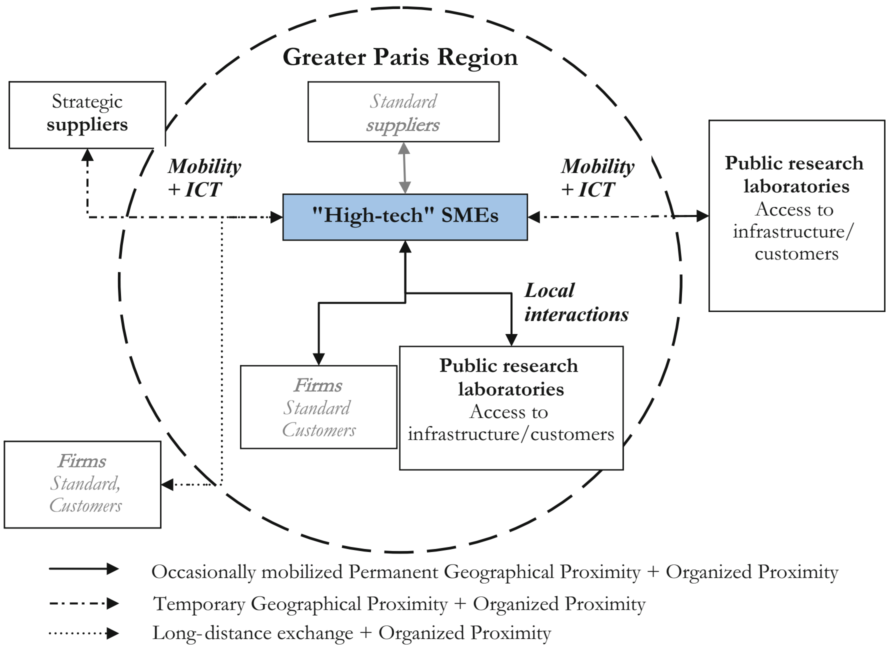

Fig. 12.6 The proximity relations of "high-technicality" SMEs

innovation process are produced internally using a technology and market watch (Fig. 12.6).

Nevertheless, Temporary Geographical Proximity plays a role in the innovation process. When interactions with research laboratories take place outside the cluster, they require long-distance contacts, especially if the firm requires access to their infrastructure in order to carry out tests and/or measurements relating to product innovations they would like to introduce. Temporary Geographical Proximity is therefore necessary in the initial and control phases of collaborative R&D projects. Face-to-face contact is also indispensable in the use of tools/infrastructure or skills of public laboratories (shared tools). These laboratories are also customers in the market for products produced by the SMEs. The requirement of firms in this category is to have access to infrastructure (or technological platforms) provided by the research laboratories, requiring travel and mobility in cases where the infrastructure in question is located outside the region.

In contrast, Permanent Geographical Proximity only plays an accessory role in the interactions between the "high-technicality" SMEs and other firms. Products from "standard" suppliers have characteristics that are known and mastered by the customers, therefore they do not require privileged and repeated interactions. In essence, the firms favour local interactions as they allow for greater responsiveness and shorter procurement leadtimes. However, the fact remains that there are greater exchanges of knowledge and information between "high-technicality" SMEs and their “partner” customers or “strategic” suppliers located in others countries than at a local level.

12.3.3.4 The Role of Proximity in Relation to Large “Leader” Firms

In the Paris region optics sector, the group of large “leader” firms is radically different to the three other categories due to its relations with technology, the state and the territory. These firms develop numerous different interactions with other firms, ranging from simple customer/supplier relationships at one end of the scale, to the establishment of common research centres or manufacturing units at the other, with product co-development projects and sub-contracting relationships located between the two extremes. They have R&D and manufacturing units located in several countries, but this global organization does not preclude the fact that they need to be located in the major production centres for goods, services or knowledge. One has to notice that these types of rims are not easily fundable in every type of clusters, especially in small industrial districts for example.

Figure 12.7 below shows the organization of a large leader firm located in the greater Paris region. It maintains relations within the strategic group with an R&D unit (Geographical Zone 3) and a manufacturing unit (Zone 4), and it also maintains external relations with standard suppliers and partners for product co-development (Zone 2). For the purpose of this study, we shall focus on external relations: the role played by proximity is very different depending on the nature of the interactions that large “leader” firms develop with other economic actors, whether located in the region or elsewhere. The complete range of proximity types is represented below.

It should be noted that two broad categories of strategic relations, involving significant exchanges of information and knowledge, result in a strong mobilization of proximity relations:

- Permanent Geographical Proximity (co-location) plays an important role in the ability of large firms to establish long-term close relations with research centres of excellence (public laboratories). An example of this is the location of *Thalès Research and Technology* or *Danone*’s global R&D Centre on the campus of the *Ecole Polytechnique*, at the core of several research centres of excellence.
- Temporary Geographical Proximity (face-to-face meetings) plays an important role, especially in relations where the large firm seeks to co-develop a new product (or to adapt it according to its needs). This is the situation for collaborative relations with “high-tech” SMEs located outside the greater Paris Region.

On the other hand, relations with standard suppliers or partner firms located in the region only involve the occasional mobilization of Permanent Geographical

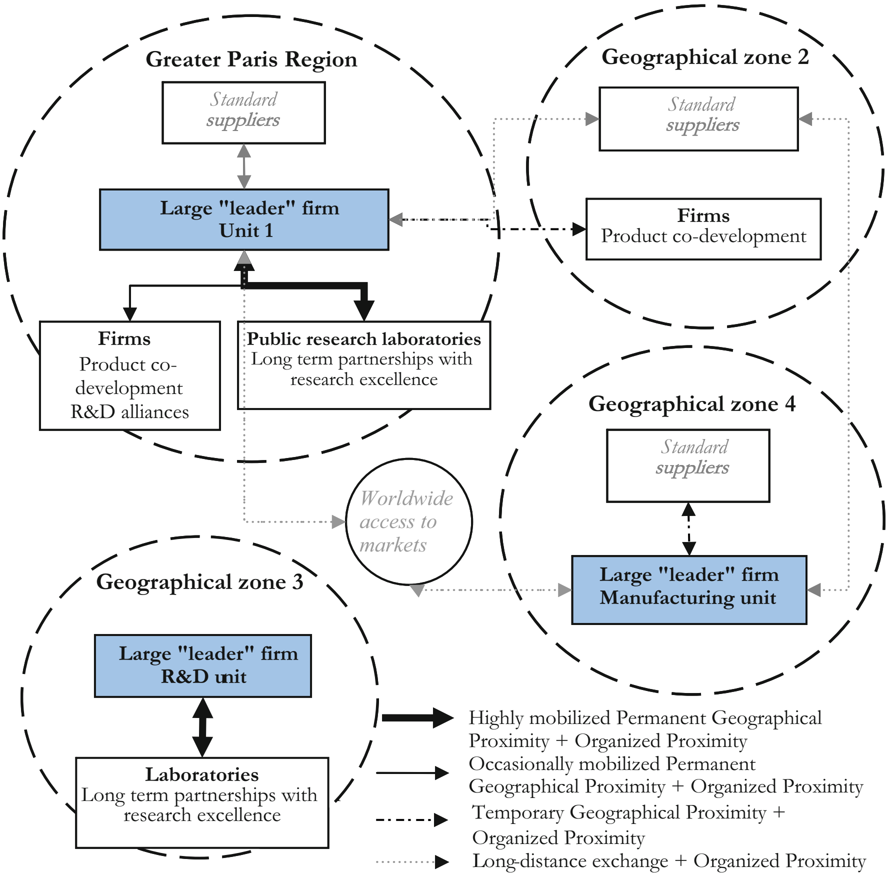

Fig. 12.7 The proximity relations of large "leader" firms

Proximity relations, while relations with standard suppliers located outside the region always require long-distance exchanges.

12.4 Conclusion

The aim of this chapter was to analyse the different proximity relations (internal vs external, geographical vs organised, permanent vs temporary) maintained by clustered innovative firms, using an applied example, and to explore the management of different types of proximities related to firms peculiarities. In order to achieve this objective, we began by outlining the main characteristics of Organized and Geographical Proximity relations and their permanent and temporary elements.

We then applied our analytical framework on innovative firms within the optics cluster in the greater Paris region, by applying the Porterian analysis method of strategic groups. We finally highlighted four groups of innovative firms that maintain specific geographical and organised relations and mobilize local relations and long-distance exchanges using mobility or ICT.

Our results are a first attempt to investigate the field of differentiated innovative firms behaviours related to proximity relations. The figures about the optics cluster in the Paris region show that the proximity approach allows for a better understanding of the strategies and the behaviours of innovative clustered firms with regards to their own peculiarities. More precisely, they reveal that the four groups of innovative firms have different profiles in terms of management of proximity relations, be there strategic interactions or more standard market relations. In particular, proximity mobilization patterns in terms of strategic interaction and partnership strongly vary depending on:

– The size of the firms
– The maturity of their technology or their technological level (from low to high tech)
– Their place in the value chain
– Their degree of specialization.

Thus, we have showed once again that the propensity to access external knowledge is unevenly distributed among clustered firms (Biggiero and Sammarra 2010). Despite the fact that all of the innovative firms develop interactions with partners, there are strong specificities in relation to knowledge exchange. A firm that is expert in a technology in an introductory or growth phase needs to develop strong external interactions (collaborative R&D, product co-development, new product operationalization) to create or reinforce its competitive advantage. On the other hand, if the product is based on mature technology, external interactions are less knowledge intensive and do not necessarily lead to the creation of a competitive advantage.

We have also confirmed the intuition that large diversified firms are likely to mobilize the resources of the various proximity types and remove local constraints. At the other end of the scale, smaller, more specialized firms are more anchored, dependent on their local relations and trapped within the cluster. There have to highly rely on Geographical Proximity in order to build permanent or repeated innovation linkages. Let us add that public policy must take into account the diversity of the various strategic groups of firms with regard to the local situations; they have to avoid excessive focus on the so-called cluster effects and the supposed positive effects of geographical proximity between firms of various sizes which often do not share the same objectives in terms of competitivity or technological choices.

Our study also paves the way for future research in the field of proximity relations related to industry and technology life cycle. “High-technology” SMEs, which are mainly characterized by a strong internal R&D organization and by their specialization in one generic technology from which they develop a wide range of products aimed at several markets, appear to be strongly dependent on both types of Geographical Proximity, be there permanent and local relations or temporary relations and external links to the cluster. On the other hand, "High-technicality" SMEs, which are characterized by a significant level of technical specialization and by the production of limited series and customized products for clearly identified market niches, appear to have accessory links at the local level, and to be rather dependent on external strategic suppliers or public labs.

Annexes

Annex 1: Method of Identification of Optic-Photonic Firms

The identification of the optic-photonic firms took three steps.

First step: we used the most representative NAF codes of the optic-photonic activity as a starting point to identify the French located firms which produce, develop and/or put these technologies on the market (codes 331A, 332B, 333Z, 334A and 334B on the data bases Kompass, Astree and Coface). More than 2,500 firms declare their activity under these NAF Codes in the Greater Paris Region (NAF Code is one of the INSEE (French National Institute of Statistics) Codes. It aims at identifying the main activity of one firm or one association).[9]

Second step: we identified the local firms whose activity is built upon optic-photonic technologies, based not only on the NAF Codes but also on various information (including web sites). The goal was to identify the firms which develop, produce or put on the market products and services based upon optic-photonic technologies.

Third step: this list was validated and completed by the extensive set of information collected through firms visits performed by *Opticsvalley*. This operation allowed us to integrate in the data base several firms which do not declare an activity related to the previous NAF Codes whereas optic-photonic technologies remain crucial in their activity.

Then, the identification by means of the only NAF Codes revealed to be incomplete. We subsequently incorporated some firms registered under the following NAF codes: 221J, 261C, 285D, 300A, 312A, 313Z, 321A, 331B, 334A, 511T, 722A, 722C, 731Z, 741G, 742C and 743B.

[9] List and description of the NAF Codes can be find at the following address: http://www.insee.fr/fr/methodes/default.asp?page=nomenclatures/naf2003/naf2003.htm

Annex 2: List of the Optic-Photonic Firms in the Greater Paris Region, on Which is Based Our Study

Company name	NAF code
AA OPTO-ELECTRONIC	311A
ABSYS	519A
ACMEL INDUSTRIES	311B
ACOME	313Z
ADVEOTEC	742C
AGATEC France	332B
ALCTRA	742C
ALTAIR VISION	722C
AMPLITUDE TECHNOLOGIES	334B
AOIP INSTRUMENTATION	332B
APRIM VIDE	332B
APS	285A
ATI ELECTRONIQUE	312A
AXMO PRECISION	518M
BALOGH SA	333Z
BIORET	731Z
CAMECA	332B
CEDIP INFRARED SYTEMS	742C
CHIMIE METAL	332B
CLARA VISION	511T
CLO ELECTRONIQUE – GROUPE ACJH	312A
COKIN	334B
CONTRINEX	518M
CORNING SAS	261J
CORNING SAS	742C
COSE CONSEIL ET SERVICE	742C
CS DEVELOPPEMENTS	742C
D-LIGHTSYS	334B
EADS SODERN	332A
EGIDE	312A
ERECA	322A
ESSILOR INTERNATIONAL	334A
ESSILOR INTERNATIONAL	334A
ESSILOR INTERNATIONAL	334A
ESSILOR INTERNATIONAL	334A
FASTLITE	518L
FORT	334B
GAUTHIER PRECISIONS	285D
GENEWAVE	731Z
GENOPTICS	332B
GERAILP [CLFA]	NA
GESEC	743B

(continued)

Company name	NAF code
GROUPE COUGET OPTICAL	524T
HAUSSER ET CIE	285D
HGH SYSTEMES INFRAROUGES	334B
HOLOGRAM INDUSTRIES	221J
HORIBA JOBIN YVON	332B
HORIBA JOBIN YVON	332B
IFRATEC	323Z
IMAGINE EYES	331B
IMSTAR SA	722A
IVEA SAS	741G
IXSEA	332B
JGB	334B
KALUTI SYSTEM	518J
KINOPTIK SYSTEMES	742C
KYLIA	334B
LASELEC IDF	334B
LASERLABS	332B
LASOPTIC	742C
LCI – LE CONTROLE INDUSTRIEL	332B
LEOSPHERE	332B
LHERITIER SAS	331A
L'OPTIQUE COMMERCIALE	334B
LORD INGENIERIE	742C
MAUNA KEA TECHNOLOGIES	731Z
MB OPTIQUE	742C
MC 2	334B
MECAPROBE ENGINEERING	285D
MEIRI	742C
MENSI SA	742C
MICRONIC	321A
MICROVISION INSTRUMENTS	742C
NANOVATION	742C
NEMOPTIC	742C
NETTEST FRANCE	741J
NEW VISION TECHNOLOGIES	743B
NEXANS FRANCE	313Z
OMMIC	321C
OPA OPTICAD/OPTO SYSTEM	742C
OPTECTRON INDUSTRIE	321A
OPTEL-THEVON	742C
OPTIMASK SA	321C
OPTIPHIC	334B
OPTIQUE DE PRECISION J FICHOU	334B
OPTITECK	334B
OXALIS LASER	742C
PHASICS	332B
PHILIPS MEDIA FRANCE	516J

(continued)

Company name	NAF code
PICOGIGA INTERNATIONAL	321C
PLASSYS	333Z
QUANTEL SA	334B
R&D VISION	731Z
R2B – OPTIQUE DE PRECISION	334B
RADIALL	312A
RENAUD LASERS	518A
SAINT-GOBAIN RECHERCHE	731Z
SAMMODE	315C
SATIMAGE	722C
SCROME	742C
SDTIE INTERNATIONAL	332B
SEDI FIBRES OPTIQUES	518J
SOCIETE D'OPTIQUE MARIS DELFOUR	334B
SOPRA	332B
SOTIMI	261J
SOVIS OPTIQUE	332B
SUEZ ENVIRONNEMENT	410Z
SYSTEME OPTRONIQUE INDUSTRIEL [SOI]	742C
TED TID	527C
THALES LASER SA	334B
THALES OPTRONIQUE SA	332A
THOMAS SINCLAIR LABORATOIRES	731Z
TOFICO	334B
TOPPAN PHOTOMASKS FRANCE	321C
TRANSLUX	261J
TRIBVN MEDICAL	221J
ULICE OPTRONIQUE	332B
UNITED VISION	741G
VERRE ET QUARTZ FLASHLAMPS	315A
VERRE INDUSTRIE	261C
VIPS FRANCE SARL	300A

References

Aggeri F, Segrestin B (2001) What is beyond multi-project management? A collective learning perspective on a recent automobile development project. Paper presented to the EIASM conference, University of Twente, Entschede

Arend RJ (2009) Defending against rival innovation. Small Bus Econ 33:189–206

Baptista R, Mendonça J (2009) Proximity to knowledge sources and the location of knowledge-based start-ups. Ann Reg Sci 45(1):5–29

Bathelt H, Schuldt N (2010) International trade fairs and global buzz, part I: ecology of global buzz. Eur Plan Stud 18(12):1957–1974

Bathelt H, Malmberg A, Maskell P (2004) Clusters and knowledge: local buzz, global pipelines and the process of knowledge creation. Prog Hum Geogr 28:31–56

Biggiero L, Sammarra A (2010) Does geographical proximity enhance knowledge exchange? The case of the aerospace industrial cluster of Centre Italy. Int J Technol Transf Commer 9(4):283–305

Bonte W (2008) Inter-firm trust in buyer–supplier relations: are knowledge spillovers and geographical proximity relevant? J Econ Behav Organ 67:855–870

Boschma R (2005) Proximity and innovation. A critical assessment. Reg Stud 39(1):61–74

Carrincazeaux C, Lung Y, Vicente J (2008a) The scientific trajectory of the French School of Proximity: interaction- and institution-based approaches to regional innovation systems. Eur Plan Stud 16(5):617–628

Carrincazeaux C, Grossetti M, Talbot D (2008b) Clusters, proximities and networks. Special Issue of Eur Plan Stud 16(5):613–621

Dankbaar B (2007) Global sourcing and innovation: the consequences of losing both organizational and geographical proximity. Eur Plan Stud 15(2):271–288

Entwistle J, Rocamora A (2006) The field of fashion materialized: a study of London Fashion Week. Sociology 40:735–751

Freel MS (2003) Sectoral patterns of small firm innovation, networking and proximity. Res Policy 32:751–770

Freire-Gibb LC, Lorentzen A (2011) A platform for local entrepreneurship: the case of the lighting festival of Frederikshavn. Local Econ 26:157–169

Gallie EP (2009) Is geographical proximity necessary for knowledge spillovers within a cooperative technological network? The case of the French biotechnology sector. Reg Stud 43(1):33–42

Giuliani E, Bell M (2005) The micro-determinants of meso-level learning and innovation: evidence from a Chilean wine cluster. Res Policy 34:47–68

Information Society Technologies Advisory Group (2006) Shaping Europe's future through ICT. ISTAG, Brussels

Kechidi M, Talbot D (2010) Institutions and coordination: what is the contribution of a proximity-based analysis? The case of Airbus and its relations with the subcontracting network. Int J Technol Manag 50(3/4):285–299

Kirat T, Lung Y (1997) Innovation and proximity. Territories as loci of collective learning processes. Eur Urban Reg Stud 6(1):27–38

Laursen K, Reichsten T, Salter A (2010) Exploring the effect of geographical proximity and university quality on university-industry collaboration in the UK. Reg Stud 45(4):507–523

Lazaric N, Longhi C, Thomas C (2008) Gatekeepers of knowledge versus platforms of knowledge: from potential to realized absorptive capacity. Reg Stud 42(6):837–852

Maskell P, Bathelt H, Malmberg A (2006) Building global knowledge pipelines: the role of temporary clusters. Eur Plan Stud 14:997–1013

Norcliffe G, Rendace O (2003) New geographies of comic book production in North America: the new artisan, distancing, and the periodic social economy. Econ Geogr 79(3):241–263

North DC (1991) Institutions. J Econ Perspect 5(1):97–112

Opticsvalley (2004) Les marchés de l'optique-photonique: Eclairage-Affichage, Les marchés de l'optique-photonique: Procédés industriels, Les marchés de l'optique-photonique: Santé et science du vivant. Optics Valley

Ponds R, Van Oort F, Frenken K (2007) The geographical and institutional proximity of research collaboration. Reg Sci 86(3):423–443

Porter M (1980) Competitive strategy: techniques for analysing industries and competitors. Free Press, New York

Porter M (1998) The role of geography in the process of innovation and sustainable competitive advantage of firms. In: Chandler AD, Hagström P, Sölvell Ö (eds) The dynamic firm. Oxford University Press, New York

RERU (2008) La Proximité, 15 ans déjà !, Special issue of the Revue d'Economie Régionale et Urbaine, 3

Rychen F, Zimmermann JB (2008) Clusters in the global knowledge-based economy: knowledge gatekeepers and temporary proximity. Special Issue of Reg Stud 42(6):767–776

Takeda Y, Kajikawa Y, Sakata I, Matsushima K (2008) An analysis of geographical agglomeration and modularized industrial networks in a regional cluster: a case study at Yamagata prefecture in Japan. Technovation 28(8):531–539
Torre A (2008) On the role played by temporary geographical proximity in knowledge transfer. Reg Stud 42(6):869–889
Torre A (2011) The role of proximity during long-distance collaborative projects. Temporary geographical proximity helps. Int J Foresight Innov Policy 7(1–3):213–230
Torre A, Gilly JP (1999) On the analytical dimension of proximity dynamics. Reg Stud 34 (2):169–180
Torre A, Rallet A (2005) Proximity and localization. Reg Stud 39(1):47–60
Vaz T, Nijkamp P (2009) Knowledge and innovation: the strings between global and local dimensions of sustainable growth. Entrep Reg Dev 21(4):441–455
Walther JB, Loh T, Granka L (2005) Let me count the ways: the interchange of verbal and nonverbal cues in computer-mediated and face-to-face affinity. J Lang Soc Psychol 24 (1):36–65
Weterings A, Boschma R (2009) Does spatial proximity to customers matter for innovative performance? Evidence from the Dutch software sector. Res Policy 38(5):746–755
Weterings A, Ponds R (2008) Do regional and non-regional knowledge flows differ? An empirical study on clustered firms in the Dutch life sciences and computing services industry. Ind Innov 16(1):11–31

Chapter 13
Impacts of Multi-level Spatial Capital Resources on Business Performance

Karima Kourtit, Peter Nijkamp, Andrea Caragliu, and Chiara Del Bo

13.1 Introduction

Firms may be seen as critical change agents in any spatial system. Consequently, the recent regional growth literature has rightly positioned firms at the centre of regional dynamics (see e.g. Capello and Nijkamp 2010). Entrepreneurship and innovation have assumed a dominant position in regional development studies. The presence of entrepreneurs is however, a necessary, but not sufficient condition for regional economic progress. Clearly, macroeconomic conditions, such as the general level of development and growth, the availability of credit and demand conditions are crucial in determining the success or failure of an economic system. Even after taking into account these major forces, however, the relevance of the behavior and performance of entrepreneurs and firms for the well-being of cities, regions and countries remains paramount. A major question, thus, is how much firms contribute to regional well-being; in other words: what are their objectives and, ultimately, what is their performance? Firms' performance, in a broad sense, is a multi-faceted concept and is influenced by conditions both internal and external to the firm. In an increasingly globalized and interlinked economy, firms, especially those with several plants, are operating in complex environments, and this should be reflected in any model attempting to unveil the determinants of performance. In

K. Kourtit (✉) • P. Nijkamp
Department of Spatial Economics, VU University, De Boelelaan 1105, 1081 HV Amsterdam, The Netherlands
e-mail: k.kourtit@vu.nl; p.nijkamp@vu.nl

A. Caragliu
Politecnico di Milano, Piazza Leonardo, 32, 20133 Milan (MI), Italy
e-mail: andrea.caragliu@polimi.it

C. Del Bo
Università degli Studi di Milano, Via Conservatorio, 7, 20122 Milan (MI), Italy
e-mail: chiara.delbo@unimi.it

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the present study, we will argue that in the context of modern high-tech industries, a firm's objective function and performance are determined by internal characteristics along with contextual conditions, at both the sectoral and spatial level. Therefore, we will first focus on the technological context and characteristics of the sector in which the firm operates, as this will directly influence its performance and goal-setting strategy. A firm's success or failure is also related to the external environment in which it operates, as this reflects the set of institutional and social norms governing its operations and determines the potential quality of the workforce and market demand conditions. We will thus include in our analysis, along with firm-specific internal factors sectoral dummy variables, an evaluation of the role of social and human capital at the regional level and the impact of the urbanization structure in which the firm operates.

Our study will also take for granted that different firm objectives, associated with different performance goals at different time horizons, should be modeled on the basis of goal-specific determinants. To this aim we will classify firm objectives into short-, medium- or long-term, by focusing, respectively, on profit growth, revenue growth, and product quality. While clearly related, these strategic goals imply different underlying decision models, warranting the formulation of three distinct empirical explanatory models.

The study is organized as follows. In Sect. 13.2 we will discuss the relevant literature in this field, and frame our contribution in the context of business performance studies, separated into firm-level determinants and broader contextual conditions. A brief overview on urbanization economies is provided as well, with the aim to stress the importance of localized context conditions for firm- and plant-level behaviour and performance. Section 13.3 sketches out the empirical model used and methodologies adopted, while Sect. 13.4 describes the novel data set collected for this study, with a particular focus on high-tech firms in the Netherlands. Section 13.5 then presents the results of the empirical estimation, carried out by means of Poisson and multi-level regression models, while Sect. 13.6 concludes and suggests possible avenues for further research.

13.2 Literature Review

The present study on the spatial dimensions on firms' behavior has a broader socio-economic and spatial ambition: it aims to encompass in the same empirical assessment model both firm-level characteristics as well as contextual conditions. For this reason, a multi-level modelling approach is adopted. This section will first summarize the main approaches to the understanding of business performance in order to provide a proper framework for our choice of firm performance determinants (Sect. 13.2.1). Next, an overview of the main theories concerning spatial contextual conditions possibly influencing a firm's performance is provided (Sect. 13.2.2); in particular, the role of social and human capital, and that of the urban and industrial context, are presented.

13.2.1 Business Performance: Firm-Level Determinants

One of the founding fathers of modern economics, Alfred Marshall, has laid the basis for efficiency analysis and hence for competitive behaviour of firms. In his 'Principles of Economics' (1920) he introduced the marginality principle as a rational economic guideline for agents (e.g., marginal cost, marginal utility). Marshall paid attention to firm behaviour and drew a distinction between internal and external economies.

The aim of this chapter is to focus on significant differences in economic performance of high-tech firms. The business performance of firms in the high-tech sector shows much variation related to their geographical location-decision choice (Kourtit and Nijkamp 2013). The growing importance of external and environmental changes puts much emphasis on entrepreneurship (information and knowledge-based activities) and has further intensified and supported the need for efficient and effective spatial capital resources, such as human capital, social capital, knowledge capital, and innovation capital, which all encourage businesses to stay competitive and profitable (Zeng and Zhao 2005). High-tech firms have to embrace these spatial capital resources in their business strategies; their strategic goals have to be growth oriented and to search and develop new (long- and short-term) opportunities in order to enhance their entrepreneurial learning strategies and business performance to remain viable and to realize sustainable competitive advantages associated with their human capital.

Further, today's turbulent business environment demands a regular adaptation of organizational strategies based on local and regional determinants, capabilities and resources, and general economic conditions. It is thus important to understand and recognize that a firm's strategic objectives must change constantly and to anticipate changing circumstances throughout the organization, from the top level down to the operational level. This also demands a better understanding, by all the firm's actors, as to their role and contribution towards the achievement of the short-term and long-term strategies and organizational goals in order to improve their business performance and to ensure a sustainable competitive advantage in regards to chosen organizational strategies, in a dynamic environment.

In a historical perspective, the development of today's business and managerial long-term and short-term strategies can be framed in the context of Sun Tzu's '*Art of War*' (1910), which leads to the understating of the importance of competition, competitive advantages and positioning in strategy to make the correct decisions and to create innovations in the competitive business environment to ensure financial viability (Kourtit and Nijkamp 2013). To provide a better insight into differences in business performance among regional patterns of spatial business activities and to understand entrepreneurial learning strategies, our research will examine the relationship between the geographic location and industrial characteristics and the business objectives and performance of individual firms in the high-tech industries.[1] The business performance in this research study is measured in terms of XXP, which refers to maximum contribution to productivity, quality and profitability (similar to the XXQ concept: see Nijkamp 2008), given the human and social capital, and other geographical and spatial resources it possesses, and commitments of the firm to strategic goals. In addition, a GIS approach will be used, in combination with multivariate econometric models, to integrate a set of different levels of information on individual firms' determinants and spatial attributes in core geographical zones.

13.2.2 Business Performance: Context Conditions

From an industrial perspective, a firm's performance has often been found to vary across sectors, mainly because of the different type of production process each sector implies. In a first influential contribution, Pavitt (1984) suggests a classification of science-based manufacturing sectors, according to empirical regularities in the fields of potential innovation sources, type of innovations, appropriability of such innovations, potential barriers to the entry of incumbents, and the average size of firms. Fifteen years later, it became clear that manufacturing was no more the only (and oftentimes, even the major) source of innovation for advanced economies, having been substituted by Knowledge Intensive (Business) Services (henceforth, KIBS; see Miles et al. 1995 for the seminal definition).

Firms active in science-based manufacturing industries and in KIBS are expected to be characterized by higher average performance indicators, being both more innovative, as well as more productive. In the present study, the industries in which each firm is active is classified according to its technological intensity, thereby allowing for a classification of sectors into two classes, which represents the basis for adding the industrial environment to the multi-level approach adopted in this study. The details on these methodologies are summarized in Sect. 13.4. From a spatial/regional perspective, moreover, two main characteristics, summarizing the environment where firm activities take place, are the subject matter of our analyses, viz. *social* and *human* capital. Clearly, the impacts of non-material forms of capital, namely of place-specific soft characteristics, can be thought of as acting ceteris paribus, viz. with an equal distribution of physical capital and hard infrastructure across the observed space.[2]

Social capital (Putnam 2000; Putnam et al. 1993; Fukuyama 1995; Bourdieu 1983, among many others) refers to the set of norms, networks, and institutions

[1] Creative industries refer usually to those economic activities that generate both tangible and intangible innovative or knowledge-oriented goods and services, which have an income-generating capacity, while cultural industries refer to those activities that have an artistic, historic-social or entertaining connotation (Kourtit et al. 2013).

[2] An hypothesis which can be considered as realistic in the relatively limited and spatially homogenous setting of the present empirical analysis.

forming the glue of a society. As such, its impacts on various performance indicators at many different levels has been tested in many studies. From this perspective, a region with a higher social capital is expected to decrease the contract costs for a firm located in the region. At the firm level, several different channels may transmit the positive effects of good quality of norms and institutions, and the availability of thick and wide networks, for firm performance. Belonging to social-capital rich regions may in fact imply belonging to environments where people share the same social language; in these contexts, it becomes less expensive to understand each other (McCloskey and Klamer 1995). “Better mutual understanding may also reduce transaction costs: whenever people get together to start a business, this is based on reciprocal trust. When this is not available, people must set up efficient rules and punishments for breaking them; and this process is costly” (Capello et al. 2011, p. 100). Finally, contract theory convincingly explains why social capital is a lubricant for completing contracts at lower costs (Bowles and Gintis 2002).

A second relevant issue considered here is the role of regional human capital in determining firm performance. The traditional human capital literature (Becker 1964; Mincer 1974) finds theoretical grounding and empirical evidence about the positive role of an educated labour force on aggregate economic performance. Such evidence is widely available also at the firm level (see for instance Crook et al. 2011 for a recent meta-analysis). More recently, because of the increasingly wide availability of an educated labour force in most Western countries, different – and more complex – forms of human capital have been analyzed. Recent contributions (Wößmann 2003; Vandenbussche et al. 2006; Caragliu et al. 2012) posit that high-level professions, creative capital, and urban knowledge capital are increasingly relevant in determining urban performance.

In this chapter, such calls for more attention to complex notions of human capital are simultaneously taken into account; the methodologies for capturing such complex relations between ‘modern’ human capital and firm performance will be summarized in the next section.

Finally, the environment where firms perform their activities matters in their location decision. According to a classical definition (Hoover 1936), firms face productivity increases because of economies of *scale* (internal to the firm); external to the firm but internal to the industry (*localization* economies), i.e. those productivity increases stemming from *specialization* externalities, and finally economies external both to the firm and to the industry, viz. *productivity* increases accruing to those firms located in large urban areas, close to other firms active in technologically-compatible industries. In this chapter the impact of urbanization economies on various firm performance indicators will also be analyzed.

13.3 Measurement Model

In order to empirically assess the relevance of each strand of literature summarized in the previous section, we resort to a multi-level modelling approach. In fact, in order to understand the determinants of the high-tech firms’ objectives and

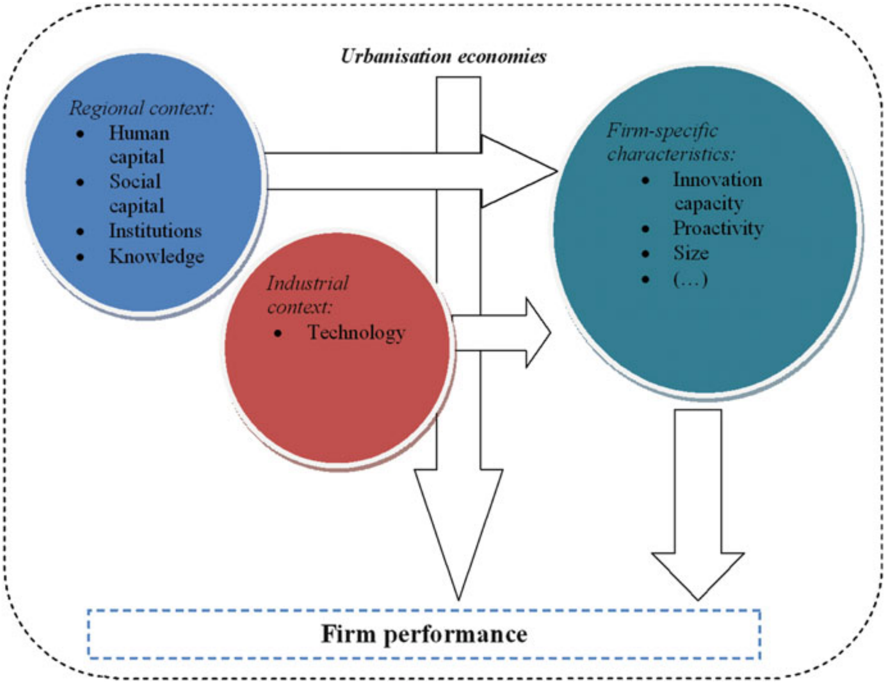

Fig. 13.1 The conceptual framework: business performance in high-tech sectors (Source: Authors' elaboration)

performance, both firm-level as well as contextual elements play a major role. Figure 13.1 summarizes the way in which such a multi-level framework is conceived. Firm performance is assumed to depend not only on firm-specific characteristics (oval figure on the right-hand side of Fig. 13.1), but also on the regional and industrial context (oval top left part of Fig. 13.1).

Also the effects of the regional (i.e., human capital and social capital endowments) and industrial contexts take place in different localizations where firms are active, with different intensities of urbanization. Since the geographical, productive, and relational context in which the firms' activities take place also influences a firm's productivity and innovativeness, the level of urbanization of such a context must also be included in our empirical analysis. Methodologically, a multi-level econometric analysis is deemed to best capture the complex set of overlapping relations, which otherwise would be difficult to disentangle and fully understand.

Multi-level statistical data sets are typically approached with mixed-effects techniques (Snijders and Boskers 2012; Rabe-Hesketh et al. 2004, 2005). Mixed-effects estimators allow the identification of possible sources of variation within groups in which individual observations can be classified. In our context, variation is expected to take place within the Dutch COROP (NUTS3 regions) where the firms being observed are located. In fact, the notions of social and human capital – and the level of urbanization – of the areas where the firms are active are by definition much more sticky than more mobile factors – for instance, capital or workers in non-specialized functions. Similarly, the industrial context where the firm is active – in particular because of localization economies (See Sect. 13.2 above) – is expected to play a major role in the definition of a firm's competitiveness. In other words: geographical and industrial locations matter for a firm's performance.

A major issue in assessing a firm's competitiveness is the very definition of 'performance'. In fact, rather different results may be achieved if observing, for instance, short-run or long-run performance indicators, monetary (quantitative) or non-monetary (qualitative) performance indicators. In our study, we will provide estimates for three different empirical models, related to three different firm performance indicators. In the absence of proper firm-specific performance indicators, we resort on the firms' stated focus on three performance objectives, namely having the growth of profits or the growth of revenues as the main goal (Models 1 and 2), or the quality of the products brought to the market (Model 3).

The mixed-effects models being estimated, firm performance can, in general, be formulated as follows:

$$y_{ij} = \beta_{0ij} + \beta_1 x_{1ij} + \beta x_{2ij} + \beta x_{3j} + \ldots + \beta_n x_{nj} \tag{13.1}$$

where Y is our measure of firm performance, the various x's are vectors of firm-specific and group explanatory variables, and the β's the parameters to be estimated. The multi-level structure is formalized by assuming that the first set of parameters obey the following law:

$$\beta_{0ij} = \beta_0 + u_{0j} + e_{0ij} \tag{13.2}$$

where both u and e are vectors of *i.i.d.* disturbances, varying respectively at the group-level only, and the group and individual levels.

Finally, as anticipated in Sect. 13.2, in this chapter we assume within-group variance to depend on the human and social capital of the region where the firm is located, on its level of urbanization, and on the industry the firm belongs to. The methods for measuring these contextual characteristics, along with the firm performance indicators and their determinants, are explained in Sect. 13.4.

13.4 The Data Set

In this section, the data set assembled for estimating the empirical model presented in Sect. 13.3 is described.

Section 13.4.1, in particular, describes the methods for collecting the individual questionnaires administered to the firms; Sect. 13.4.2, instead, presents the methodologies used to calculate the indicators used in the subsequent empirical analyses, in order to measure complex characteristics such as human and social capital, and the industrial characteristics of the interviewed firms.

13.4.1 Methods for Data Collection

Our empirical research aims to explore significant differences and relevant impacts of multi-level spatial capital resources on Dutch high-tech firms' performance (Sect. 13.3), broadly distinguishing between shorter- and longer-term strategic goal settings. This research extensive database for the multi-level model to be used consists of an original comprehensive spatial data set – micro-data on firms with meso-data on regional covariates – with various moderator variables in different NUTS3 regions (or COROP level) in the Netherlands. The georeferentiated data about geographical and regional socio-economic indicators regarding, location characteristics, and meso-environmental factors (both municipal, with 467 municipalities, and regional, 40 Dutch regions) have been obtained mostly from Statistics Netherlands (CBS) for the year 2008.

We also obtained detailed micro-data on important business characteristics of a large set of individual firms in the high-tech sector in the Netherlands for the year 2008. Most observations are concentrated in highly urbanized areas of the Country (see Fig. 13.2).

Detailed micro-based information was collected through extensive semi-structured interviews with firms' officials and executives in charge of the business strategy and economical decisions of the organization. The in-depth field survey was addressed to 61 prominent Dutch organizations, made up of 19 large firms and 42 SMEs, with an average of 4 key officers per firm from which both location and performance factors were collected. A self-composed performance statements questionnaire – identified from the broad literature available, first tested at a company level and re-formulated – was used to obtain clear information from the firms on their critical performance success conditions and indicators that reflect business innovations in a competitive economic system (for details, see also Kourtit and Nijkamp 2011). Each representative had to give a rating on a 5-point Likert scale, varying from '1 = not at all' to '5 = very strong' according to a long list of statements. The interviewees were also asked if they had experienced other important business and managerial conditions and benefits. Finally, a collection of 240 information documents on their business characteristics was gathered, as well as motivational and driving forces that are demonstrating the decisive role for turning the firm into a high-performance firm.

Plant-level information was then obtained by aggregation of indiviudual managers' responses for each plant analyzed. Because both original micro- and macro-scale data formats consist of different geographical scales (separate and disaggregated), a GIS-oriented statistical analysis was used to aggregate these

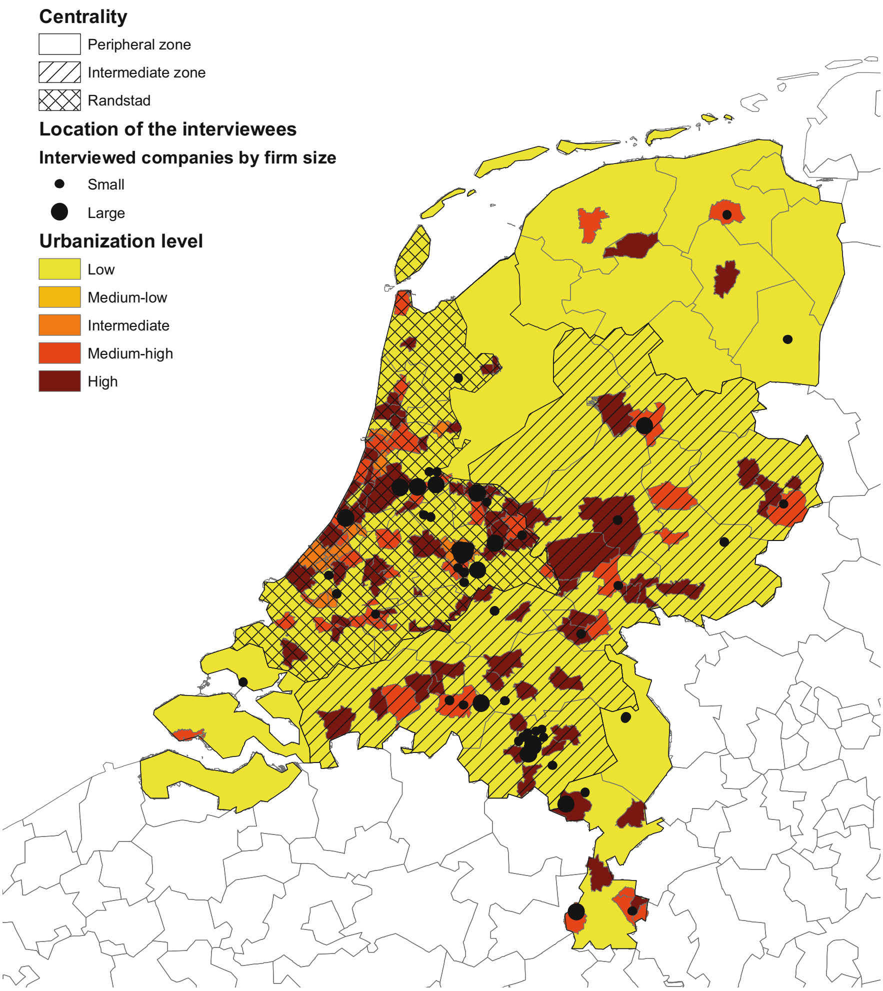

Fig. 13.2 Spatial distribution of firms in the Netherlands (Source: Authors' elaboration)

data for the target zone, the COROP-level (which contains 40 Dutch regions) in order to uncover a variety of information, and to identify geographically discriminating factors in the firms' performance. Thus, it was also possible to offer a compact, systematic overview of the general micro and macro-scale data, as depicted in Fig. 13.3.

This conceptual information framework was inspired by the recently developed '*Flying Disc*' multilevel model by Kourtit and Nijkamp (2013), and used in our conceptual framework (Fig. 13.3) in order to extract significant relationships between firm performance and spatial capital resources and drivers, and to better understand the linkages between geographic and location business environments

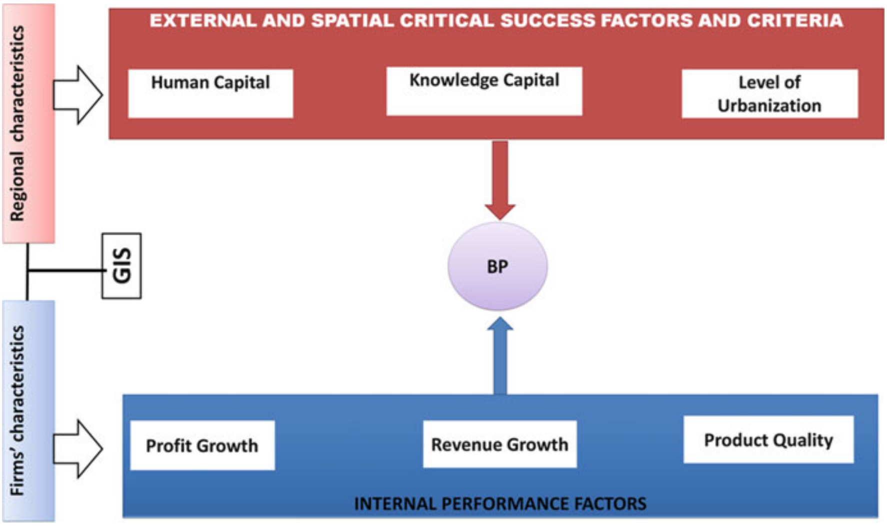

Fig. 13.3 Structure of the systematic database for Dutch regions and high-tech firms (Source: Authors' elaboration)

and the firms' short-term and long-term strategic viable options and performance – and also to assess location decisions in line with their business strategy. More details can also be found in Kourtit et al. (2013). The results will be presented in Sect. 13.5.

13.4.2 Complex Indicators

Given the multi-level structure of the data set, four complex indicators have been built, and collected, in order to capture region-specific and industrial characteristics, namely, the region's human capital, social capital, level of urbanization, and the industry in which each firm is active.

13.4.2.1 Human Capital

Given the increasing complexity of the modern production system, a comprehensive measure of human capital cannot be summarized by the region's average level of schooling. Therefore, in this chapter we adopt the definition of human capital stated for the first time in Caragliu et al. (2012). This implies capturing four dimensions of human capital, viz. the average level of education of the region, the share of high-level professionals, the wealth of creative capital, and the urban knowledge capital. Table 13.1 shows the indicators used to measure each of the four components of human capital.

Table 13.1 Measures of human capital

Aspect of human capital	Indicator	Source of raw data
Level of education	Regional average years of schooling	European Values Study (EVS), 2008/2009 wave
High-level professionals	Share of workforce in medium-high and high-tech industries	Dutch Central Bureau of Statistic (CBS)
Creative capital	Principal Components Analysis on creative capital characteristics[a]	Dutch Central Bureau of Statistic (CBS)
Urban knowledge capital	Number of multinational companies in the fortune top 500 list with control branches in the COROP region	ESPON Project FOCI

Source: Authors' elaborations
[a]These include the yearly numbers per 1,000 inhabitants of:
Visits to the region's museums
Total book loans from public libraries
Visits to the region's cafes
Total tourist inflows
The first principal component obtained is associated to the only eigenvalue higher in modulus than 1 (this is equal to 3.26). The total share of variance in the data explained by thus vector is equal to 0.65. Details of the performed PCA are available upon request from the authors

These indicators are then summarized by means of a Principal Components Analysis (PCA). The first vector, which represents our measure of human capital, explains 54 % of the total variance in the four vectors, and is associated with an eigenvalue equal to 2.14.

13.4.2.2 Social Capital

Social capital has traditionally encountered difficult measurement issues. Given its multi-faceted nature, a complete list of definitions and corresponding indicators may require much more space than a single article. In order to follow a comprehensive definition, we resort to Putnam's work, which defines social capital as encompassing *norms, trust*, and *networks*. Besides, since investing in human capital is deemed to be associated with higher levels of social capital (Coleman 1988), we also include a proxy for human capital investments in this measure.

Therefore, we have to look for a proxy for each of those axes, and next perform a PCA on the COROP region-varying measures described below in Table 13.2. The resulting first vector explains almost 40 % of the total variance in the data.[3]

[3] A remarkable level, given the highly orthogonal vectors included in the PCA.

Table 13.2 Measures of social capital

Aspects of social capital	Indicator	Source of raw data
Norms	Share of followers of the Dutch Reformed Church	Dutch Central Bureau of Statistic (CBS)
Trust	Percentage of citizens satisfied with life	Dutch Central Bureau of Statistic (CBS)
Networks	Share of citizens active at least on a monthly basis in voluntary associations	Dutch Central Bureau of Statistic (CBS)
Investment in human capital	Number of education institutions in the COROP region	Dutch Central Bureau of Statistic (CBS)

Source: Authors' elaborations

Table 13.3 Levels of urbanization (5 classes)

Intensity of urbanization	Value classes	Encoded as
Very strong	Average density of addresses of 2,500 or more per sq. kms	5
Strong	Average density of addresses between 1,500 and 2,500 per sq. kms	4
Intermediate	Average density of addresses between 1,000 and 1,500 per sq. kms	3
Little	Average density of addresses between 500 and 1,000 per sq. kms	2
None	Average density of addresses lower than 500 per sq. kms	1

Source: CBS, "Stedelijkheid van een gebied". Retrieved on Oct. 26, 2012 at the URL: http://www.cbs.nl/nl-NL/menu/methoden/begrippen/default.htm?conceptid=658. Authors' elaborations

13.4.2.3 Level of Urbanization

In this case an indicator of the intensity of the COROP region's level of urbanization is made available by the Dutch Statistical Institute (CBS). Urban density is measured as reported in Table 13.3.

13.4.2.4 Industries

All firms in the data set (a total of 61) can be classified as high-tech. In fact, the few industries in traditional sectors (e.g. automotive, food processing, construction etc.) are active in high-technology market niches. The frequency of the firms in the interviewed sample per industry is shown in Fig. 13.4.

In order to further discriminate in terms of the firm's technological content, the 16 industries are clustered into six larger *meso* industries, which in turn collapse into two main classes, which we label as '*traditional high-tech*' and '*new high tech*'. New high-tech industries are those characterized by the highest intensity of

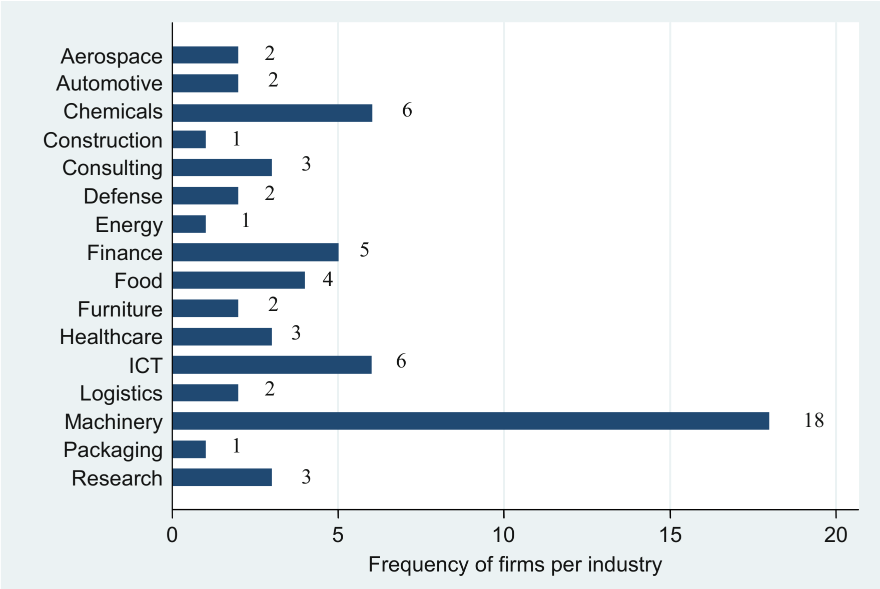

Fig. 13.4 Frequency of the interviewed firms per industry (Source: Authors' calculations)

innovativeness, and include ICTs, defense, chemicals, consulting, research, energy, and finance.

13.5 Estimation Results

13.5.1 Introduction

In this section we propose a simple taxonomy of possible firms' objectives, broadly distinguishing between shorter- and longer-term goals. If the firm's owners and shareholders have a short-term perspective, profit maximization and growth may be identified as the primary objective. In this case, firm-level determinants include structural characteristics, such as firm size, with larger firms with a consolidated market share and status expected to be more focused on increasing profits; innovative activities and expenditures, with a higher focus on innovation conducive to the growth of firms; and a firm's attitude towards the external market environment, in particular associating the profit objective with a more proactive attitude.

A more medium-term objective is, instead, related to increasing revenues and sales and, ultimately, the market share. Important determinants are still innovativeness and proactivity, with the addition of a proxy for the internal institutional quality, in terms of a clear and understandable organizational structure. A medium-term objective revolving around the determination of the appropriate price level and quantity produced to increase sales, revenues and market shares will be facilitated inside a firm with a well-defined structure of control and command.

In a multi-level context, short-term objectives are also probably related to industry-specific factors, which suggest the use of the two-classes indicator described in Sect. 13.4.2.4.

Having instead product quality as the primary objective suggests a longer-term perspective and requires the definition of a different model to understand the main determinants at the firm level. Increasing product quality requires that the internal organization of the firm is geared towards encouraging cooperation and coordination among the different actors and divisions; the existence, inside the firm, of a high quality monitoring system, which can ensure that all the appropriate steps are taken effectively; and the use of a reliable system of indicators of firm activity.

In a multi-level framework, human capital at the NUTS3 level is the relevant contour condition conducive to a quality objective. A more qualified workforce is able to understand and pursue this more complex objective; this is expected to be associated also with the presence in the region of more educated customers, which care more about quality aspects (if sales are space-specific) and in general to an external environment which stimulates and supports this kind of long term firm strategy (De Donder and Roemer 2009).

The intensity of urbanization is also considered as a potential determinant of both short- and long-term objectives, as explained in the urbanization economies literature and briefly summarized in Sect. 13.2.[4]

13.5.2 Profit Growth

Table 13.4 shows estimation results for the analysis of the determinants of the first firm objective we consider, namely profit growth. Aiming at increasing profits is usually identified as the primary objective of a firm's owner and shareholders, and is ultimately a growth objective (for a classical reference, see Baumol 1962).[5]

We proceed, in the first four columns, by adding one variable at a time in the Poisson model, including a full set of industry dummies in each specification. The

[4] Although spatial heterogeneity and spatial dependence may potentially affect our data, they cannot be addressed with spatial econometric techniques because of an insufficient number of observations, which would invalidate any spatial statistical inference. Some degree of spatial autocorrelation can be nevertheless visualized on the maps shown on a contribution in this same line of research (see Kourtit et al. 2013).

[5] Although as previously anticipated spatial processes may in principle characterize the firm objectives here analyzed, we do not observe any form of spatial autocorrelation in any of the three dependent variables in the tested models. Using both contiguity as well as distance matrices, and letting in the first case the threshold distance move over the minimum and maximum distance over which contiguity can be calculated for the observed data, we find no statistical significance associated to any standard Moran's I statistic.

Table 13.4 Results of empirical estimation on profit growth

Dep. variable	*Profits growth*				
Model	a1	b1	c1	d1	e1
Type of estimator	Poisson	Poisson	Poisson	Poisson	Mixed effects
Constant term	1.18***	1.04***	0.50*	0.65***	5.53***
	(0.00)	(0.00)	(0.07)	(0.02)	(0.00)
Firm's innovativeness	0.12***	0.11***	0.13***	0.13***	0.65***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Firm's proactivity	–	–	0.11**	0.12***	0.50**
			(0.01)	(0.00)	(0.01)
Firm size	–	–	0.34***	0.38***	2.18***
			(0.00)	(0.00)	(0.00)
Level of urbanisation	–	–	–	−0.06	−0.34**
				(0.11)	(0.04)
Random effect in:					
High-tech industries	–	–	–	–	1.06***
					(0.00)
High-social capital COROP regions	–	–	–	–	0
					(1.00)
High-human capital COROP regions	–	–	–	–	0
					(1.00)
Number of obs	61	61	61	61	61
Pseudo R2	0.07	0.07	0.09	0.09	0.33
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Robust standard errors	Yes	Yes	Yes	Yes	–

Standard errors are in parentheses. Statistical significance levels are labeled with ***, **, and *, referring to the 1 %, 5 % and 10 % level, respectively

fifth column reports instead the results of the mixed effect multilevel model with all the independent variables.

Considering a firms' innovative activity, a higher focus on innovativeness and related activities at the firm level increases the probability of focusing on profit growth as an objective. The direction of causality is *a priori* unclear, as we expect more innovation to lead to higher profitability, which in turn might allow additional resources to be devoted to innovative expenditures. The positive and significant coefficient associated to the innovativeness variable is in line with previous literature which postulates that as increases in profits and innovation are positively correlated, and that the two effects, in a dynamic setting, are mutually reinforcing (Cainelli et al. 2006). This positive relationship appears particularly relevant in high-tech industries (Audretsch 1995; Coad et al. 2008). The results in our sample confirm these expectations, since the coefficient associated with innovation is positive, highly significant, and remarkably stable across specifications (Colums a1–d1, Table 13.4).

Adding a variable explicitly referring to firms' strategic management approach (firm's proactivity) allows a better understanding of targeting an increase in profits. A proactive market strategy, related to a firm's ability to actively discover and cater to the market's latent needs, by reacting to changes in consumers' preferences, ultimately leading to the uncovering of new market opportunities (Atuahene-Gima et al. 2005), is positively related to an increase in the probability of pursuing a profit growth objective. This result may be unveiling the implicit link between proactivity and increase in market share, thus compatible and positively associated with increase in profits.

Finally, larger firms, on average, are more likely to concentrate on profit expansion and growth. While the earlier literature on this subject has suggested that firm size should be unrelated to growth, more recent studies have instead highlighted the importance of the life cycle of the firm (Geroski 1998) and have ultimately found support for the size-growth nexus (Pagano and Schivardi 2003).

Since our data set includes large production plants, which typically belongs to large – often multinational – companies, a more densely urbanized location is found to be negatively associated with profit growth. This is fully in line with the agglomeration economies findings on the specialization of mature industries in less urbanized areas, vs. diversification of innovative sectors in denser agglomerations, summarized, among others, in Rosenthal and Strange (2004).

Finally, while no evidence is found on a differential role for social and human capital, strong evidence is instead found for the fact that *ceteris paribus*, a higher average profit growth characterizes firms active in high-tech industries. This effect is about 20 % as large as the overall average profit growth.

13.5.3 Revenue Growth

In Table 13.5 we model the determinants of another firm objective, namely the growth of revenues. Along with the aim of increasing profits, a focus on increasing the stream of revenues is a typical short/medium-term firm objective, pursued, in particular, by management. We focus on its relation to internal innovative activities (firm's innovativeness), attitude toward the external market (firm's pro-activity) and an internal institutional factor, namely a proxy for organizational and bureaucratic complexity (the firm has imperfect knowledge of the structure organization).

With respect to firm-level internal innovative activities, a higher focus on innovation is related to a higher probability of a revenue increasing objective, in line with results for profit growth (Table 13.4) and previous literature (Del Monte and Papagni 2003; Corsino and Gabriele 2011). The statistically significant positive coefficient is however, slightly decreasing, as additional determinants are added, from columns b2 to d2 in Table 13.5, suggesting that this factor is not the main determinant for revenue maximization. Firm's proactivity is also positively correlated with revenue growth, suggesting that a proactive market strategy is complementary to an increase in sales objective. A complicated and cumbersome internal firm structure, not fully understood by its members, appears instead to be an impedance factor to firm growth, although the coefficient becomes significant only in the multi-level mixed model specification (Column e2, Table 13.2).

Table 13.5 Results of empirical estimation on revenues growth

Dep. variable	*Profits growth*				
Model	a2	b2	c2	d2	e2
Type of estimator	Poisson	Poisson	Poisson	Poisson	Mixed effects
Constant term	0.67***	0.73***	0.59***	0.77***	3.37***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Firm's innovativeness	0.16***	0.16***	0.13***	0.13***	0.55***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Firm has imperfect knowledge of the organisation structure	–	−0.02	−0.06	−0.06	−0.50**
		(0.66)	(0.19)	(0.19)	(0.01)
Firm's proactivity	–	–	0.12***	0.12***	0.34*
			(0.00)	(0.00)	(0.07)
Level of urbanisation	–	–	–	−0.05	0.11
				(0.18)	(0.46)
Random effect in:					
High-tech industries	–	–	–	–	1.23***
					(0.00)
High-social capital COROP regions	–	–	–	–	0
					(1.00)
High-human capital COROP regions	–	–	–	–	0.01
					(0.99)
Number of obs	61	61	61	61	61
Pseudo R2	0.07	0.07	0.09	0.09	0.33
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Robust standard errors	Yes	Yes	Yes	Yes	–

Standard errors in parentheses. Statistical significance levels are labeled with ***, **, and *, referring to the 1 %, 5 % and 10 % level, respectively

Internal and external institutional factors have been recently considered in performance studies at the firm level, and have been shown to be an important determinant of a firm's success. Borghi et al. (2011) stress the importance of external, country level institutional quality and ownership structure, as an internal institutional factor, for firm level productivity in the electricity distribution sector. By considering the firm as an integration mechanism (Grant 1996), it is clear that a complex organizational structure, which hinders the ability of agents to communicate and coordinate effectively, will ultimately hamper the firm's ability to pursue a strategy of growth, in this case in terms of revenues.

In the case of revenues growth, no significant effect of the level of urbanization on firm performance is found. Instead, once again firms active in high-tech industries (previously defined as '*new high-tech*') achieve on average higher levels of revenues, with a magnitude comparable to the overall estimated constant term.

In conclusion, firms appear to have strengthened their focus on what is important for the organization (consciousness of personnel) and on the achievement of organizational results (set-up priorities), a higher operational efficiency (flexible management to anticipate on changes) and a better achievement of organizational goals (constant focus on the question: what are we doing? clear organizational and individual performance indicators). Firms experienced the financial advantages frequently indirectly. The indirect increase in financial performance is mainly due to the non-financial advantages (e.g., better organizational structure, enhanced strategic intensive feedback and learning, smart objectives coupled with sustained improvement in decision-making, continuous focus on management structure and efficiency, direct communication lines, better process and costs orientation) and depends on various external factors (e.g., rapidly growing markets, increased competition, impacts of technology, shifts in customer expectations and economic growth).

Furthermore, human capital in the organization has become more pro-active, is more committed to the organization, and is more oriented towards processes which help achieve organizational results. The strengthened involvement and understanding of people of the strategy, coupled with the improvement in the quality, motivated employees, pro-activity, better steering on projects and more innovativeness, considerably facilitates the achievement of organizational goals. However, it could be argued that focus and result-orientation are higher on achieving organizational results than for large firms, because they have simpler organizational structures, fewer customers and are flexible and more adaptable to market and environmental changes.

Finally, firms have to clarify the management's responsibility and link authority and responsibility with improved accountability. The firms tends to experience an increase in revenue (approximately equal to 5 %) and a decrease in cost (approximately equal to 5 %), resulting in an increase in total profit. The decrease in costs is specifically caused by higher operational efficiency, better management of the organization, and more effective management control. The strengthened focus on what is important for the organization, coupled with the improvement in the decision-making, considerably facilitates the achievement of organizational goals.

13.5.4 Product Quality

Moving on to a broader, longer term perspective, an important firm-level objective is related to increasing product quality. Manufacturing high-quality products, especially in high-tech industries, ensures the creation of a base of satisfied consumers, which helps build the firm's reputation and ultimately helps increase sales and market shares through reputational and word of mouth mechanisms (Rogerson 1983; Kirmani and Rao 2000). Successfully investing in higher product quality involves specific organizational and internal strategies that may well differ from those aimed at achieving shorter term goals, such as profit and revenue maximization, discussed in Sects. 13.5.2 and 13.5.3.

To this end, our empirical model for the determinants of product quality is different from the previous set-up, and includes different firm-level determinants (Columns a3–d3) and context conditions (Column e3, Table 13.3). A first facilitating factor geared towards quality improvements is related to the cooperativeness of the different compartments and actors inside the firm. The higher the degree of internal cooperation and coordination, the higher we expect the ability to invest in a long term product quality to be. Sethi (2000) convincingly documents how product quality is positively related to information integration of internal cross-functional teams, as this enhances a common understanding and consistency of decisions made by the team. This prior is confirmed by our analysis, as the coefficient associated with cooperation is positive and statistically significant in all specifications, although its importance is decreasing with the introduction of new determinants. A well-functioning and high quality monitoring system is also an important pre-requisite for successful product quality improvements, and should enhance the probability that firms with such a system in place may focus on this longer-term objective. This factor, however, appears only mildly related to the quality objective in our sample, and is statistically significant, with the expected positive sign, only in one specification (Column b3). Once the existence of a sub-optimal performance indicator system is accounted for, the effect of a monitoring system loses significance. A poor performance indicators system might imply a misalignment between objectives and actual progress made, and is expected to be negatively associated with a quality objective. This is confirmed by our empirical results, but only in the multi-level modeling specification (Column e3).

The level of urbanization has once again no impact on product quality. What is interesting here is that instead the measure of group variance is found most significant, which is, unlike the short-term firm objectives commented in Sects. 13.5.2 and 13.5.3, the level of human capital. Firms located in COROP regions with higher levels of human capital are found to be more likely to pursue long-term, rather than short-term, objectives, and target product quality as a firm goal. This relation is found to be strongly significant and is once again rather relevant also in terms of magnitude (Table 13.6).

Not all (important) organizational performances are determined and (well) measured, in particular the ‘soft’ performance indicators, and not all indicators are relevant for these firms. Clearly, the feedback of the results and measurement of various issues (hard and soft indicators) have to be clarified, before an unambiguous statement can be made.

It is clear that firms have to pay too much attention to various drivers of business performance, if the information base does not contain sufficient strategic information to take a consistent and precise business direction and to consider what and how to improve. This situation gives apparently an unbalanced view of the total organization’s performance, with a focus on mainly a financial perspective. Firms do recognize the importance of non-financial measures of performance for both managing and evaluating their achievements, as financial figures alone did not identify the elements that may lead to good or poor future financial results.

This suggests that firms want to improve continuously the performance of the organization and to achieve sustainable success to become and stay world-class in everything they do through a particular approach or mentality. They need to be able to anticipate on changing circumstances in their industry and to stay ahead of the extreme – often global – competition, to have the right information at the right time to make the best decisions and take the best actions for the benefit of the development of continuously and sustained organizational improvement and enhance quality of the organization, to know if strategic goals are going to be met and if they are able to satisfy the stakeholders of the organization and strengthen stronger accountability.

Table 13.6 Results of empirical estimation on product quality

Dep. variable	Product quality				
Model	a3	b3	c3	d3	e3
Type of estimator	Poisson	Poisson	Poisson	Poisson	Mixed effects
Constant term	0.69***	0.58***	0.74***	0.65***	5.60***
	(0.17)	(0.18)	(0.20)	(0.26)	(0.00)
Firm actors are more cooperative	0.12***	0.07*	0.08*	0.09**	0.38*
	(0.04)	(0.04)	(0.04)	(0.04)	(0.09)
Firm has a high-quality performance monitoring system	–	0.08*	0.06	0.06	0.24
		(0.04)	(0.04)	(0.04)	(0.34)
Firm has non-reliable internal performance indicators	–	–	−0.07	−0.07	−0.59**
			(0.05)	(0.05)	(0.02)
Level of urbanisation	–	–	–	0.02	0.25
				(0.04)	(0.19)
Random effect in:					
High-tech industries	–	–	–	–	0
					(1.00)
High-social capital COROP regions	–	–	–	–	0.53
					(0.36)
High-human capital COROP regions	–	–	–	–	0.92***
					(0.01)
Number of obs	61	61	61	61	61
Pseudo R2	0.02	0.02	0.03	0.03	0.11
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Robust standard errors	Yes	Yes	Yes	Yes	–

Standard errors in parentheses. Statistical significance levels are labeled with ***, **, and *, referring to the 1 %, 5 % and 10 % level, respectively

A higher organizational quality improves internal processes such as the communication process on the organization's strategy, the performance information supply process, and the strategic planning process. As a result, employees are more satisfied, while the quality of the products and services provided by the organization increase by contributing to a strengthened reputation of the firm as a quality organization.

Besides, too much financial information does not give a balanced view of the organization's performance. It is also too voluminous, making it too expensive and bureaucratic. In addition, the system causes the wrong behaviour in people as peer pressure escalates in internal competition and mutual strive. Too much financial information may be due to a lack of standardization (taxonomy) of non-financial information, and the fact that there are many systems in organization.

Finally, information systems that contain too many performance indicators do not give strategic information. In addition, the performance information cannot be trusted as it tends to become unreliable. This basically renders the performance information meaningless. People cannot focus on too many data; therefore they do not have a clear view (no priorities) and focus on the business. The art is to get tailor-made information that leads to a meaningful strategy orientation and better focus. In addition, the system causes the wrong behaviour in people as peer pressure escalates in internal competition and mutual strive.

13.6 Concluding Remarks

This study has made an evidence-based attempt to identify the drivers of the performance of firms in the high-tech sector in the Netherlands. On the basis of a unique and detailed database, a new multi-level model was constructed that encompassed various new forms of capital resources, including urban and regional resources. This framework was used to empirically estimate the impact of both firm-specific and context conditions on the firms' performance. The performance indicators used in our study were: profit growth, revenue growth and product quality. The empirical results offered a wealth of insights into the determinants of the firms' achievements.

Clearly, more empirical research would be needed to come up with generalizable results. On the one hand, the urban and regional context conditions would need further empirical investigation, such as physical infrastructure, digital accessibility etc. Another factor that would deserve more attention in future modelling experiments is the network configuration in which firms operate. And finally, it would be interesting to acquire more insights into the institutional support framework for high-tech business.

References

Atuahene-Gima K, Slater SF, Olson EM (2005) Th e contingent value of responsive and proactive market orientations for new product program performance. J Prod Innov Manag 22(6):464–482

Audretsch D (1995) Innovation, growth and survival. Int J Ind Organ 13:441–457

Baumol WJ (1962) On the theory of expansion of the firm. Am Econ Rev 52(5):1078–1087

Becker GS (1964) Human capital: a theoretical and empirical analysis, with special reference to education. University of Chicago Press, Chicago

Borghi E, Del Bo CF, Florio M (2011) Institutional quality and productivity: implications for public firms in the electricity sector. Paper presented at the Xth Milan European Economy Workshop, Università degli Studi di Milano, Milano, 8–9 June 2011

Bourdieu P (1983) Ökonomisches kapital, kulturelles kapital, soziales kapital. In: Kreckel R (ed) Soziale Ungleichheiten (Soziale Welt, Sonderheft 2). Otto Schartz & Co, Goettingen, pp 183–198

Bowles S, Gintis H (2002) Social capital and community governance. Econ J 112(483):419–436

Cainelli G, Evangelista R, Savona, M (2006) Innovation and economic performance in services: a firm-level analysis. Cambridge Journal of Economics 30(3):435–458

Capello R, Nijkamp P (2010) Handbook of regional growth and development theories. Edward Elgar, Cheltenham

Capello R, Caragliu A, Nijkamp P (2011) Knowledge and social capital: increasing returns in regional growth. Stud Reg Sci 41(1):93–114

Caragliu A, Del Bo C, Nijkamp P (2012) A map of human capital in European cities. In: Van Geenhuizen M, Nijkamp P (eds) Creative knowledge cities. Myths, visions and realities. Edward Elgar, Cheltenham, pp 213–250

Coad L, Burgess ND, Fish L, Ravillious C, Corrigan C, Pavese H, Granziera A, Besancon C (2008) Progress towards the convention on biological diversitys 2010 and 2012 targets for protected areas. Parks Durb Plus 5 Int J Prot Area Cover 17(2):35–42

Coleman JS (1988) Social capital in the creation of human capital. Am J Sociol 94(1):S95–S120

Corsino M, Gabriele R (2011) Product innovation and firm growth: evidence from the integrated circuit industry. Ind Corp Change 20(1):29–56

Crook TR, Todd SY, Combs JG, Woehr DJ, Ketchen DJ (2011) Does human capital matter? A meta-analysis of the relationship between human capital and firm performance. J Appl Psychol 96(3):443–456

De Donder P, Roemer JE (2009) Mixed oligopoly equilibria when firm's objectives are endogenous. Int J Ind Organ 27(3):414–423

Del Monte A, Papagni E (2003) R&D and the growth of firms: empirical analysis of a panel of Italian firms. Res Policy 32(6):1003–1014

Fukuyama F (1995) Trust: the social virtues and the creation of prosperity. Free Press, New York

Geroski PA (1998) An applied econometrician's view of large company performance. Rev Ind Organ, Springer 13(3):271–294

Grant RM (1996) Toward a knowledge-based theory of the firm. Strateg Manag J 17:109–122

Hoover EM Jr (1936) The measurement of industrial localization. Rev Econ Stat 18(4):162–171

Kirmani A, Rao AR (2000) No pain, no gain: a critical review of the literature on signaling unobservable product quality. J Mark 64(2):66–79

Kourtit K, Nijkamp P (2011) Creativity and diversity: strategic performance management of high-tech SMEs in Dutch urban areas. In: Kourtit K, Nijkamp P, Stough R (eds) Drivers of innovation, entrepreneurship and regional dynamics. Springer, Berlin, pp 45–64

Kourtit K, Nijkamp P (2013) In search of creative champions in high-tech spaces: a spatial application of strategic performance management. J Reg Sci (forthcoming)

Kourtit K, Nijkamp P, Caragliu A, Del Bo C (2013) Spatial contextual impacts on business performance of Dutch firms. Reg Stat 52:13–26

Marshall A (1920) Principles of economics, 8th edn. Macmillan, London

McCloskey D, Klamer A (1995) One quarter of GDP is persuasion. Am Econ Rev 85(2):191–195

Miles I, Kastrinos N, Bilderbeek R, Hertog P, Flanagan K, Huntink W, Bouman M (1995) Knowledge-intensive business services: users, carriers and sources of innovation. European Commission, Brussels, https://www.escholar.manchester.ac.uk/api/datastream?publicationPid=uk-ac-man-scw:75252&datastreamId=FULL-TEXT.PDF. Retrieved 19 Oct 2012

Mincer J (1974) Schooling, experience and earnings. Columbia University Press, New York

Nijkamp P (2008) XXQ factors for sustainable urban development: a systems economics view. Rom J Reg Sci 2(1):325–342

Pagano P, Schivardi F (2003) Firm size distribution and growth. Scand J Econ, Wiley Blackwell 105(2):255–274, 06

Pavitt K (1984) Sectoral patterns of technical change: towards a taxonomy and a theory. Res Policy 13(6):343–373

Putnam RD (2000) Bowling alone: the collapse and revival of American community. Simon & Schuster, New York

Putnam RD, Leonardi R, Nanetti RY (1993) Making democracy work: civic traditions in modern Italy. Princeton University Press, Princeton

Rabe-Hesketh S, Skrondal A, Pickles A (2004) Generalized multilevel structural equation modeling. Psychometrika 69(2):167–190

Rabe-Hesketh S, Skrondal A, Pickles A (2005) Maximum likelihood estimation of limited and discrete dependent variable models with nested random effects. J Econ 128(2):301–323

Rogerson WP (1983) Reputation and product quality. Bell J Econ 14(2):508–516

Rosenthal SS, Strange WC (2004) Evidence on the nature and sources of agglomeration economies. In: Henderson JV, Thisse JF (eds) Handbook of regional and urban economics, vol 4. Elsevier, Amsterdam, pp 2119–2171, ch. 49

Sethi R (2000) New product quality and product development teams. J Mark 64(2):1–14

Snijders TAB, Bosker RJ (2012) Multilevel analysis: an introduction to basic and advanced multilevel modeling. Sage, London

Vandenbussche J, Aghion P, Meghir C (2006) Growth, distance to frontier and composition of human capital. J Econ Growth 11(2):97–127

Wößmann L (2003) Specifying human capital. J Econ Surv 17(3):239–270

Zeng DD, Zhao JL (2005) Effective role resolution in workflow management. INFORMS J Comput 17(3):374–380

Chapter 14
Using a Structural Equation Model to Analyze Potential Determinants of Spatial Variations in Endogenous Regional Growth Performance

Patricio Aroca, Robert Stimson, and Roger Stough

14.1 Introduction

There have been relatively few attempts to develop operational models explicitly designed to measure endogenous regional economic performance and to identify those factors that potentially might explain spatial variations in that performance across a national space economy. This chapter does that by experimenting with structural equation modelling as an alternative to the commonly used ordinary least square (OLS) regression modelling.

Structural equation modelling helps address two problems that occur in OLS regression modelling approaches:

(a) The first is the measurement problem that is evident in many of the explanatory variables used in models investigating regional economic performance that gives rise to biased estimators. This is the endogeneity problem.
(b) The second is the multi-collinearity problem that tends to be inherent among explanatory variables in models, thus making estimators unstable or non-robust.

These problems are common in much spatial econometric analysis and are only partially addressed in procedures that adjust for endogeneity

P. Aroca (✉)
Business School, Universidad Adolfo Ibáñez, Av. Padre Alberto Hurtado 750, Viña del Mar, Chile
e-mail: patricio.aroca@uai.cl

R. Stimson
Australian Urban Research Infrastructure Network, Faculty of Architecture, Building and Planning, University of Melbourne, Parkville VIC 3010, Australia
e-mail: rstimson@unimelb.edu.au

R. Stough
George Mason University, School of Public Policy, 4400 University Drive, MS 6D5, Fairfax, VA 22030, USA
e-mail: rstough@gmu.edu

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Thus, the structural equation modelling approach can have the advantage of providing deeper insights into the nature of the relationships between variables that are surrogate measures for factors that might be hypothesized as having a significant impact on, for example, the endogenous regional employment growth performance of regions and in explaining the spatial variability that exists across a space economy in the patterns of that performance. Here we test this notion using a data set covering the decade 1996–2006 for Functional Economic Regions (FERs) in Australia.

The chapter proceeds as follows. First we refer to some of the key literature on (a) endogenous regional economic development, and especially recent attempts to develop frameworks for an operational model to analyze the potential determinants of spatial variations in endogenous regional growth performance, and (b) some of the methodological issues in conducting such modelling. Next we provide a justification for using structural equation modelling as an alternative to the more commonly used regression modelling approaches. That is followed by a brief discussion of the data set for FERs in Australia that we use to model endogenous regional economic performance, 1996–2006. There is then a brief discussion of the spatial pattern of that performance of FER scores across Australia on the dependent variable. We then present the results of the structural equation modelling, including a comparison of the results that had been obtained from earlier analyses using the same data set but based on OLS regression modelling, including adjustments to address spatial autocorrelation. The chapter concludes with a brief discussion of what might be the significance of the structural equation modelling approach for spatial econometric analysis of regional performance.

14.2 Literature Overview

14.2.1 Growth Theory

Successively over the last couple of decades or so regional growth models have been placing increasing emphasis on endogenous factors and processes as being important influences on a region's economic development and as potential explanatory factors differentiating regions. Over the years a rich literature has developed in economics and in particular in regional science in what has been referred to as 'the new growth theory' or 'endogenous growth theory', That includes, for example, the following: Arrow (1962), Romer (1986, 1990), Lucas (1985, 1988), Barro (1990), Rebelo (1991), Grossman and Helpman (1991), Arthur (1994), Malecki 1991; Johansson et al. (2001), Capello and Nijkamp (2009), Stimson et al. (2005), Stimson and Stough (2009a, b), Stimson et al. (2011).

In addition to the long held notion – derived from the comparative advantage proposition embedded in the early work on trade theory – that differentiation between regions may be explained by variations in a region's resource endowments (originating in the writings of David Ricardo), the 'new growth theory' has placed emphasis on other explanatory factors, including the following:

- Regional industrial structure and specialization/diversification (Kaufman 1993; Lande 1994; Henderson et al. 1995; Gordon and McCann 2000)
- R&D, technology, and product cycles (Thomas 1975; Erickson 1994; Norton and Rees 1979; Erickson and Leinbach 1979; Rees 1979, 2001; Markusen 1985)
- Population, market size, scale effects and agglomeration (Scott 1988; Porter 1990; Krugman 1991; Patten 1991; Duranton and Puga 2000; Maier 2001; Taylor et al. 2002)
- Human capital (Malecki 1998a, b; Hanushek and Kimko 2000; Goetz and Rapasingla 2001)
- Learning (Simmie 1997; Florida 1995; Jin and Stough 1998; OECD 2000; Maillat and Kibir 2001)
- Creative capital (Florida 2002)
- Entrepreneurship, innovation and innovative milieu (Schumpeter 1934; Kirzner 1973; Smilor and Wakelin 1990; Krugman 1991; Castells and Hall 1994; Jessop 1998)
- Leadership (Parkinson 1990; Saxenian 1994; Fairholm 1994; Jessop 1998; Heenan and Bennis 1999; de Santis and Stough 1999; Stimson and Stough 2009b)
- Institutional factors, including social capital (Doig and Hargrove 1987; North 1990; Parkinson 1990; Fainstein 1983; Bolton 1992, 1999; Putnam 1993; Coleman 1988; Amin and Thrift 1995; Huxam 1996; Jessop 1998; Rodrick 1998; de Santis and Stough 1999; Clingermayer and Feiock 2001; Bentley 2002; Brooklym et al. 2002; Hofstede 1997; Pollitt and Bouckaert 2002; Vasquez-Barquero 2002; Stimson and Stough 2009b).

In effect, the role of endogenous factors might be seen as enhancing the competitive advantage or otherwise of a region as discussed by Porter (1985, 1986, 1990) and as suggested by Stimson et al. (2006).

However, somewhat surprising the literature is relatively devoid of empirical studies that explicitly seek to measure endogenous regional economic growth and to operationalize a model to explain why there are spatial variations in endogenous regional growth performance across a nation. Recent work by Stimson et al. (2005) and Stimson and Stough (2009a, b) proposes such a model framework in which it is suggested that factors such as leadership, institutions and entrepreneurship might act as intervening or mediating variables between factors that relate to a region's resource endowments (in the widest sense) and its market fit characteristics and the outcome variable, namely a surrogate measure of endogenous regional employment growth (or decline). There are, of course, deficiencies in the secondary data sets that are typically available in most countries – as that provided in national data collections such as the census – which makes it difficult to derive what may be regarded to be adequate measures for variables that might relate to some of these factors, particularly factors such as entrepreneurship, leadership and institutions.

Nonetheless, a number of recent empirical studies (that are exploratory) have used OLS regression modelling, including a spatial regression modelling approach, in attempts to develop and apply an operational model to investigate spatial variations in endogenous regional growth performance across regions. In Australia there have been analyses across non-metropolitan regions (Stimson et al. 2009a, b) and across FERs (Stimson et al. 2009a, b; Stimson et al. 2010). In the U.S. there has been an analysis of the metropolitan statistical areas (MSAs) (Shyy et al. 2009).

In this chapter we attempt to build on this literature and at the same time address some of the collinearity and endogeneity problems of earlier attempts to empirically model and test the endogenous growth concept at the regional level. We now turn to a description of the structural equation model and how it is adapted to address the modelling problems encountered previously.

14.2.2 Methodology

In much of the spatial econometric literature investigating regional economic performance, OLS regression analysis has tended to be used as the traditional approach to model growth. But in using spatial data in such modelling that is usually based on *de jure* regions (such as states or counties in the U.S. and Statistical Divisions or Local Government Areas in Australia) the spatial autocorrelation problem is encountered. However, there is a considerable literature in regional science proposing procedures to incorporate in regression modelling adjustment to manage the spatial autocorrelation problem (see, for example, Anselin 1988a, b).

However, we suggest that regression modelling approaches are not flexible enough to accommodate the problems and the challenges that an extended model of endogenous growth imposes, such as that proposed in the Stimson and Stough (2009b) model framework in which the mediating effects of specific factors need to be explicitly tested.

Measure for concepts like human capital, social capital, creative capital, institutions, leadership and entrepreneurship are not readily available or where they are there are multiple measures related to different aspects of these concepts. Therefore econometric theory recommends using proxy variables. However, proxy variables are measured with error, and the more proxy variables are included in a model, the less accuracy will be the results. In addition, multi-collinearity makes the results less stable. Ridge regression (Greene 2002) has been proposed as a solution, which means creating factors with a set of proxy variables. However the main criticism of that approach is the difficulty of interpretation of the factors that are created by use of the method.

In addition to the measurement problem (endogeneity) there is another issue that arises as a weakness of the traditional regression growth equation models. The endogenous growth, human capital, social capital, creative capital, institutions, leadership, entrepreneurship and the other factors that are hypothesized as affecting endogenous growth are likely to be highly inter-correlated, and their relationship is bi-directional, because these factors reinforce each other.

We suggest an alternative modelling approach might be employed to help address these problems inherent in the traditional OLS regression modelling approaches. That is structural equation modelling (see Kline 2005; Oud and Folmer 2008; Kaplan 2009; Bollen et al. 2010; Byrne 2010). That approach simultaneously takes into account the measurement error problem and the relationship between factors. Factors are built from a confirmatory factor analysis, and therefore they have a clear interpretation. In addition, the collinearity among the factors is taken into account through a simultaneous equation system.

14.3 A Structural Equation Modelling Approach

In adopting a structural equation modelling approach, following Bollen et al. (2010) the specification of the model can be presented as two sets of equations.

(a) A first set of equations that form part of the system is called the *Measurement Model* and it links the factors or latent variables with the observed variables. This sub-model is used for taking care of the multicollinearity problem that arises in the OLS methodology when there are several variables associated to one concept such as social capital, creative capital, institutions, leadership, and entrepreneurship, among others. This is basically a Confirmatory Factor Analysis (CFA), where the latent variables, like the concepts enumerated above, are estimated based on a set of variables collected for this purpose. Before running this procedure, a consistency analysis of the data is done, using the Cronbach Alfa. In order to assure that the variables used to measure a concept have a significant communality which come from the latent variable that we are trying to measure. Once the variables to measure a concept are chosen, then the data is ready for the next step.

The equations of the measurement model, in general terms, are:

$$y = \alpha_y + \lambda_y \, Endogenous\ Growth\ Factors + \varepsilon_y => y = \alpha_y + \lambda_y \eta_i + \varepsilon_y$$

$$x = \alpha_x + \lambda_x \, Exogenous\ Factors + \delta_x => x = \alpha_x + \lambda_x \xi_i + \delta_x$$

where:

y and x are vector of the observed variables associated to the factors
α_y and α_x are intercept vectors
λ_y and λ_x are matrices of factor loadings or regression coefficients measuring the impact of the endogenous (η_i) and exogenous (ξ_i) factors (or latent variables) on the observed variables. In the example that we will develop, we have an observed variable for endogenous growth, therefore the equation for y, will

not be necessary, and we will use directly the measure proposed by Stimson and Stough (2009b), which is the shift-share regional residual after discounting the growth associated to the nation and the sector.

(b) The second set of equations is called the *Structural Model*. Using exogenous factors created in the previous model, the multicollinearity, typically a problem in OLS or spatial regression for using the measured variables is avoided. Therefore, using the measure for endogenous growth and the factors created in the previous step, the model can be written as:

$$\begin{aligned} Endogenous\ Growth\ Measures = \alpha + \beta\ Endogenous\ Growth\ Measures \\ + \Gamma\ Exogenous\ Factors + \zeta \end{aligned}$$

$$\eta_i = \alpha + \beta^* \quad \eta_i + \Gamma^* \quad \xi_i + \zeta_i$$

where:

α, β and Γ are matrices of coefficients for the intercepts, the impact of the endogenous (η_i) and exogenous (ξ_i) factors respectively

The ζ is the vector of disturbances.

In order to estimate this equation system we assume that:

$E(\boldsymbol{\zeta}) = 0$

COV(Exogenous Factors, $\boldsymbol{\zeta}$) $= 0$, and

$(I - \beta)$ is invertible.

Figure 14.1 shows graphically how this model looks like. In the circles are showed three measurement model while in the oval is the structural model. There are several estimation procedures to estimate simultaneously the model, and in the optimization process are taking into account both type of models, therefore the estimated latent variables will be the ones that optimize the explanatory power of the structural model. Details of the estimation procedure can be found in Kaplan (2009), Kline (2005) and Bollen et al. (2010).

In this stage, the factors that are in the structural model as latent variables also might be interpreted as instrumental variable in the traditional econometrics model, which help to deal with the endogeneity of the model, as the latent variables help to deal with the instability of the coefficient in a OLS context due to the high correlation among the variables that are used to estimate de latent variables.

14.3.1 The Data and Functional Economic Regions

In testing an application of the structural equation modelling approach discussed above we use a data set relating to FERs (Functional Economic Regions) for Australia that has been described in details and used in the previous work by

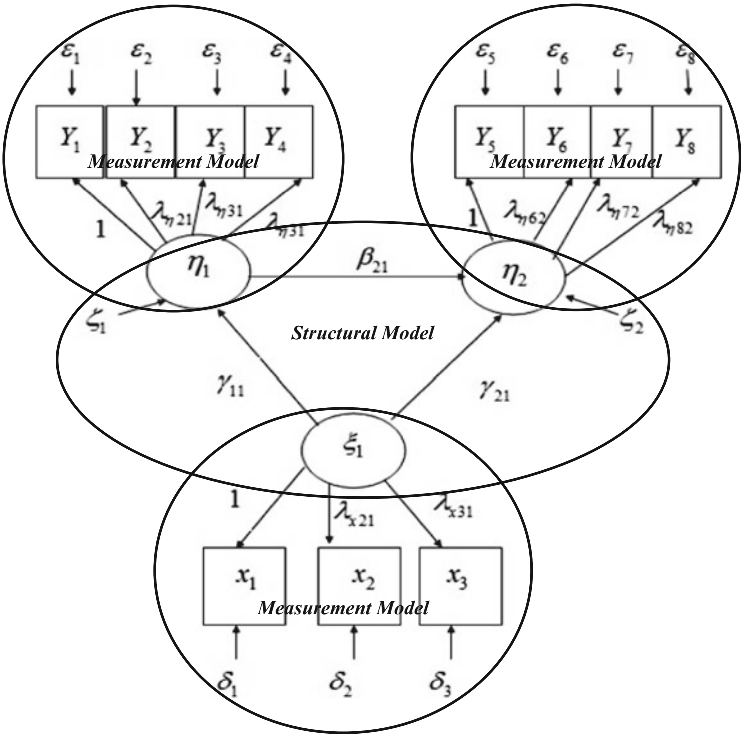

Fig. 14.1 Measurement and structural models (Source: The Authors)

Stimson et al. (2009a, b, 2010) in which OLS regression analysis, along with a spatial error and an spatial lag model, was used to investigate the potential determinants of spatial variations in the pattern of FER performance in Australia over the decade 1996–2006 (Table 14.1 shows the specification of variable used in the modelling process). That modelling had attempted to partially operationalize the model framework proposed by Stimson et al. (2005) and Stimson and Stough (2009b). Unfortunately the available national data sets do not include variables from which it is possible to derive measures of some of the endogenous factors that were proposed in that model framework. That is particularly the case for the leadership, entrepreneurship and institutional factors.

The level of geography used in the modelling undertaken for this chapter is a new national regional geography – the FER – and which has been used in the OLS regression modelling conducted by Stimson et al. (2009a, b, 2010). The Intramax method, which uses a hierarchical clustering procedure proposed (see Barros et al. 1971; Masser and Brown 1975; Masser and Scheurwater 1980; Ward 1963), was used to compile the new FER geography (see Mitchell and Flanagan 2009 for full details). As discussed by Stimson et al. (2010), these functional regions are characterized by a high degree (75–85 %) of employment self-containment.

Table 14.1 Definition of the variables used in the modelling

Variable label	Variable description
Dependent variable	
REG_SHIFT	Regional Shift Component derived from a Shift Share Analysis of employment change summed across industry sectors (1996–2006)/Labour Force (1996)
Explanatory variables	
SPEC_96	Specialization Index for 1996 (Herfindahl-Hirschman Index)
SPEC_CH	Change in Specialization Index from 1996 to 2006 (Herfindahl-Hirschman Index)
SCI	Structural Change Index (1996–2006)
SCI_CH	Change in the Structural Change Index (from 1996–2011 to 2001–2006)
L_INC_96	(Approximate) Mean Individual Income – 1996 Annual (Log) (real)
L_INC_CH	Change in (Approximate) Mean Individual Income – 1996–2006 Annual (Log) (real)
UNEMP_96	Unemployment rate in 1996 (%)
UNEMP_CH	Change in Unemployment rate from 1996 to 2006 (pps)
L_POP_96	Log of population (1996)
L_POP_CH	Change in Log of population (1996–2006)
LQ_MAN_96	Location Quotient for the Manufacturing Industry in 1996
LQ_INF_96	Location Quotient for the Information, Media and Telecommunications Industry in 1996
LQ_FIN_96	Location Quotient for the Financial and Insurance Services Industry in 1996
LQ_PRO_96	Location Quotient for the Professional, scientific and technical services Industry in 1996
LQ_MAN_CH	Change in the Location on Quotient for the Manufacturing Industry, 1996–2006
LQ_INF_CH	Change in the Location Quotient for the Information, media and telecommunications Industry, 1996–2006
LQ_FIN_CH	Change in the Location Quotient for the Financial and insurance services Industry, 1996–2006
LQ_PRO_CH	Change in the Location Quotient for the Professional, scientific and technical services Industry, 1996–2006
POSTGRAD_96	Proportion of labour force with a Postgraduate Degree of higher in 1996
BACHELOR_96	Proportion of labour force with Bachelor Degree of higher in 1996
TECHQUALS_96	Proportion of labour force with technical qualifications in 1996
POSTGRAD_CH	Change in the Proportion of labour force with a postgraduate degree of higher, from 1996 to 2006
BACHELOR_CH	Change in the Proportion of labour force with a bachelor degree of higher, from 1996 to 2006
TECHQUALS_CH	Change in the Proportion of labour force with technical qualifications, from 1996 to 2006
SYMBA_96	Proportion of Symbolic Analysts (Managers + Professionals) in Employment in 1996

(continued)

Table 14.1 (continued)

Variable label	Variable description
SYMBA_CH	Change in the proportion of Symbolic Analysts (Managers + Professionals) in Employment from 1996 to 2006
VOLUNTEER_06	Proportion of Volunteers in Working Age Population (15–64) in 2006
CREATIVE_06	Proportion of Total Employment in Creative Industries in 2006
A_COAST	Border is adjacent to coastline (No = 0; Yes = 1)
P_METRO	Border is within/adjacent to Metropolitan Statistical Division (No = 0; Yes = 1)
D_URBAN	Classified as Urban under Australian Classification of Local Government system (1= Yes, 0 = No)
D_REMOTE	Classified as Remote under Australian Classification of Local Governments system (1 =Yes, 0 = No)

Source: Stimson et al. (2009a, b, 2010)

The high degree of self-containment within the spatial units thus formed is potentially beneficial as it means that the census attributes for a FER both apply to people who live and work in that region. However the aggregation of the Statistical Local Areas (SLAs) – on which FERs are built – reduces the amount of data to a mere 141 data-points for the FERs across Australia. In addition, we might expect low spatial autocorrelation, by construction of these FERs.

14.3.2 Model Variables

All except four of the variables used in the modelling reported in this chapter were derived from data readily available in Census of Population and Housing data (1996, 2001 and 2006) and are the same as those used in the previous OLS regression modelling by Stimson et al. (2009a, b, 2010). Their selection was based on a review of the literature on endogenous regional economic growth – which has identified factors that are hypothesizes and empirically validated as being (potential) factors that might be regarded as dimensions or constructs that influence endogenous regional economic performance, including those proposed by Stimson et al. (2005) and Stimson an Stough (2009b) in their model framework for endogenous development (See Table 14.1).

14.3.3 The Dependent Variable

Difficulties are encountered in the use of data from the Census of Population and Housing to derive a satisfactory measure of the outcome state which is the *dependent variable* in a model investigating regional economic performance. A variable measuring regional economic growth or performance over a period of time is needed, and following Stimson et al. (2005) and Stimson and Stough (2009a, b) the proxy measure of endogenous regional growth (and decline) used as the *dependent variable* [REG_SHIFT] is the *differential* or *regional shift component* derived from a *shift-share analysis* of employment change over the decade 1996–2006, standardized by the size of an FERs labour force at the 1996 census. The Haynes and Dinc (1997) method is used for the shift-share analysis.

14.3.4 The Explanatory Variables

The set of 32 *exploratory variables* used in the modelling are listed in Table 14.1. All but four are derived from Census data, and they include both static and dynamic variable measures for a range of FER characteristics. These variables purport to measure the effects of constructs that the literature has suggested are factors that may affect endogenous regional employment growth/decline performance:

- Industrial structure including industry specialization and structural change
- Population size and growth
- Labour force participation
- Human capital
- Income distribution
- Occupational shifts
- Social capital
- Creative capital.

As seen in Table 14.1, there are some variables that explicitly measure some of those factors, while for others there are proxy variables relating to the factors.

In addition four locational proxies are included that might impact on endogenous regional employment growth or decline. Those relate to the position of a FER within the national settlement system, including a remoteness index measure, proximity to a metropolitan region, and location with respect to the coast.

For reasons of space, the rationale for the selection and specification of the explanatory variables used in the modelling and listed in Table 14.1 is not provided here as that has been discussed in detail in Stimson et al. (2009a, b, 2010).

14.4 Results of the Structural Equation Modelling

The structural equation modelling approach used in this chapter to investigate the potential determinants of spatial variation in the performance of FERs across Australia in the dependent variable REG_SHIFT uses the variables listed in Table 14.1 as explanatory variables in the modelling.

In what follows we first outline the *general model* and show how an initial model is derived. After that we show how to proceed to get a better fit of the model with the data. We then show how a *final model* may be derived.

Table 14.2 Collected variables allocated to factors using Cronbach Alfa

Factors	Variables	In the factor
R1 – Industry specialization and structural change measures	SCI	x
	SPEC_96	x
	SPEC_CH	
	SCI_CH	
R2 – Income measures	L_INC_CH	x
	L_INC_96	x
R3 – Unemployment measures	UNEMP_CH	x
	UNEMP_96	x
R4 – Industry employment and location quotient measures	LQ_PRO_96	x
	LQ_FIN_96	x
	LQ_INF_96	x
	LQ_MAN_96	x
	LQ_MAN_CH	x
	LQ_INF_CH	x
	LQ_FIN_CH	x
	LQ_PRO_CH	x
R5 – Human capital measures	POSTGRAD_96	x
	BACHELOR_96	x
	TECHQUALS_96	x
R6 – Human capital changes measures	POSTGRAD_CH	x
	BACHELOR_ CH	x
	TECHQUALS_ CH	x
R7 – Location attributes	A_COAST	x
	P_METRO	x
	D_URBAN	x
	D_REMOTE	x
POPULATION CHANGE	L_POP_CH	x
Variables not in the model		
Social capital measure	VOLUNTEER_06	x
Creative capital measure	CREATIVE_06	x
Ocupational structure measures	SYMBA_96	x
	SYMBA_CH	x

Source: The Authors

We start with a *general model* where the endogenous growth is approximated by the variable REG_SHIFT as the dependent variable in the model, and it is explained by a set of variables for which we do not have direct measures.

In order to create measures for those latent variables, we first collect a set of variables that are affected for the latent variables that we call factors. Table 14.2 shows the set of variable collected by Stimson et al. (2009a, b, 2010) used for estimated the factor.

Before running the estimation of the structural and measurement model, we run a consistency analysis over the definition done in Table 14.2. That definition is done on the basis of the experience and theory explaining the association of the concepts or factors and the available variables.

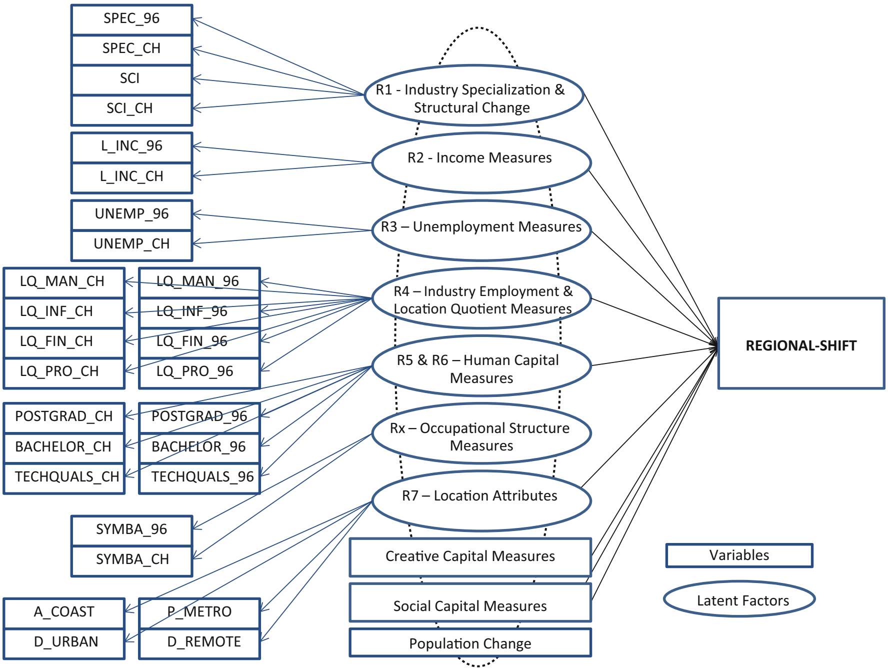

Fig. 14.2 The general specification of the endogenous growth model (Source: The Authors)

However, the set of variables that are forming the factors are not all that initially have being collected for then. Using the Cronbach Alfa, we test for the consistency of the variables within the factor. The consistency analysis carried out allows us to evaluate if the variable have enough communality to be part of the latent variable. The column – In the factor – shows the results of this preliminary consistency analysis of the collected data. Most of the variables are consistent measure of the defined factor, except for the first factors where two of the collected variables show a very low communality with the other two variables, so we decide to let them out of the factor.

In the procedure that we have used until here, we have chosen the variables that might be used to proxy the latent variables and in addition, we have imposed a structure defining how the latent variables affect the endogenous growth that is measured by the regional shift share, as it is shown in Fig. 14.2. Imposing structure in the model is the way econometricians distinguish themselves from pure statisticians, given that structure comes from theory, endogenous growth theory in this case, not from the analysis of the data.

Then, we estimate the general model and select the variables to stay in the model according their statistical significance (p-value lower than 0.05). The chosen model is in Table 14.3.

Table 14.3 Estimation of the final model

Factors and explanatory variables			Estimate	S.E.	C.R.	P	Standarized
Structural model							
REG_SHIFT	←	R1	−2.075	.322	6.444	***	−.730
REG_SHIFT	←	R2	.870	.312	2.785	.005	.266
REG_SHIFT	←	R3	−.908	.202	−4.493	***	−.329
REG_SHIFT	←	R4	−.772	.243	−3.176	.001	−1.597
REG_SHIFT	←	R5	25.100	9.089	2.761	.006	.817
REG_SHIFT	←	R7	.285	.145	1.974	.048	.585
REG_SHIFT	←	L_POP_CH	2.091	.286	7.304	***	.632
Measurement model							
SCI	←	R1	1.000				.815
SPEC_96	←	R1	1.050	.114	9.177	***	.721
L_INC_CH	←	R2	1.000				.776
L_INC_96	←	R2	−1.772	.190	−9.336	***	−.879
UNEMP_CH	←	R3	1.000				.924
UNEMP_96	←	R3	−1.105	.044	−24.980	***	−1.026
LQ_PRO_96	←	R4	1.058	.060	17.712	***	.930
LQ_FIN_96	←	R4	.952	.057	16.586	***	.906
LQ_INF_96	←	R4	1.000				.885
LQ_MAN_96	←	R4	.516	.107	4.809	***	.388
POSTGRAD_96	←	R5	1.000				.919
BACHELOR_96	←	R5	4.256	.150	28.281	***	1.008
TECHQUALS_96	←	R5	3.276	.541	6.055	***	.460
A_COAST	←	R7	.377	.131	2.871	.004	.253
P_METRO	←	R7	1.000				.800
D_URBAN	←	R7	1.099	.097	11.303	***	.870
D_REMOTE	←	R7	−.867	.123	−7.029	***	−.584
POSTGRAD_CH	←	R6	1.000				.691
BACHELOR_CH	←	R6	7.122	.644	11.062	***	.997
TECHQUALS_CH	←	R6	7.903	1.109	7.125	***	.615
LQ_MAN_CH	←	R4	−.252	.057	−4.416	***	−.359
LQ_INF_CH	←	R4	.105	.044	2.363	.018	.199
LQ_FIN_CH	←	R4	.088	.038	2.318	.020	.195

Source: The Authors
***Imply p-value lower than 0.001

14.5 Discussing the Results of the Structural Equation Modelling

We discuss the results derived from the process undertaken for the structural equation modelling outlined in the previous section. First we provide a synthesis of the model. Then we examine the role of the factors and the relationships between the factors and variables in the model.

14.5.1 A Synthesis of the Model

The model that arises from the search analysis process shown in Table 14.3 for the endogenous regional economic growth dependent variable (REG_SHIFT) is affected by several factors; some of them have a positive effect and some others have a negative one. In addition, there is significant correlation among them.

The main final estimated structural equation for the model has the following form:

$$REG\,SHIFT = \gamma_1 R_1 + \cdots + \gamma_5 R_5 + \gamma_7 R_7 + \gamma_8 L\_POP\_CH + EE_1$$

The first general appreciation of these results, from the Structural Model of Table 14.3, is that we have a set of inputs that directly affect the endogenous regional growth dependent variable REG_SHIFT:

(a) The *positive* effects on endogenous regional growth performance are the human capital availability in region, the attributes of the location of a region in the national settlement system, and the variation in population size of a region and the level of incomes in a region.
(b) The *negative* effects on endogenous regional growth performance are the degree of industry sector specialization and structural change, and the level of unemployment, and the industry sector location quotient measures. The stronger these characteristics are then the slower the regional endogenous growth will be.

It should be noted that all these results are conditioned by the relationship among the factors that did not affect regional endogenous growth directly, namely creative capital, social capital and change in human but through their correlation with the other factors that determine endogenous growth directly, which we will describe later.

However, in order to understand these results it is necessary not only to examine the nature of the relations in the main equation (Structural Model) but also to look at how the factors are related to the measures that are used to build them (Measurement Model)

14.5.2 The Role of Factors or Latent Variable and Their Relationship with the Collected Variables

We now turn to discuss the role of each factor and its relation with the variables used to build it. The reader will need to refer to Tables 14.1 for the names and 14.2 for the relation between factors and variables provided earlier in the chapter.

14.5.2.1 R5: Human Capital Factor

According Table 14.3, human capital in a region at the beginning of the period 1996–2006 is the most important factor (with the highest standardized score of .817) explaining variation in endogenous regional growth performance across FERs in Australia over the decade 1996–2006. Within this factor the most important variables are the proportion of people with post-graduate (POSTGRAD_96) and bachelor (BACHELOR_96) qualifications. While technical human capital (TECHQUALS_96) is important, it has about half of the impact of the other two educational qualifications variables.

14.5.2.2 R7: Location Attributes Factor

As shown in Table 14.2, this factor is composed of four variables (A_COAST, P_METRO, D_URBAN, D_REMOTE). Looking at the standardized coefficients, we see that the importance of this factor is higher for metropolitan and other urban regions, and while still positive it is lower for regions located on the coast. However, this factor is negative for regions in remote locations. Therefore, regions that are in or part of metropolitan city regions areas, plus regions that are other urban areas (and especially the larger regional cities and towns) are likely to have larger endogenous regional growth for the period 1996–2006. Not surprisingly a remote area location tends to have a negative effect on endogenous regional growth performance, and many of those remote regions are sparsely populated and in some cases are places characterized by a preponderance of indigenous community settlements.

14.5.2.3 Population Change (L_POP_CH) Variable

This variable which is the change in the log of the population of a region is as important as the human capital factor in explaining variations in endogenous regional growth performance across FERs in Australia over the decade 1996–2006. This is not surprising as population growth, which tends to be dominated in some regions by the impact of internal migration flows and/or immigration, is well known to often be a driver of regional economic growth as seen, for example, in sun-belt growth areas in coastal Queensland and New South Wales and in parts of Western Australia.

14.5.2.4 R2: Income Measures Factor

The income factor has a positive impact on endogenous regional growth performance across FERs in Australia. This is to be expected as the higher the level of regional income, then the larger the pressure on local demand. However, this factor is not as important as the human capital or location factors in affecting endogenous regional growth. In addition, the change in income (L_INC_CH) in the period 1996–2006 is the one that pushes local endogenous employment growth. However, the larger the initial income level (L_INC_96) then the lower will be the endogenous regional growth performance of a region. The reason behind this result could be that an initial high income in the region could be associated with a specific industry sector or national growth, so that there is less space for endogenous growth, thus creating this negative impact of the L_INC_96 variable.

The other three factors or latent variables in the structural model have a negative effect on regional endogenous employment growth performance across FERs in Australia. The first two are related to industry sector employment concentrations and industry specialization/diversification in a region.

14.5.2.5 R4: Industry Sector Employment and Location Quotient Measures Factor

This factor relates to the incidence of employment in specific industries in the producer services including information, media and telecommunications, in financial and insurance services, and in professional, technical and scientific services, plus in manufacturing industries. From Table 14.3 it is evident that for this factor the dominant influence is for the initial condition in the location quotient (LQ) based on regional employment. The results in Table 14.3 show that the beginning of the period LQ for professional services (LQ_PRO_96), finance (LQ_FIN_96) and information (LQ_INF_96) sectors are the most important explaining the impact of this factor on endogenous regional growth performance across FERs in Australia over the decade 1996–2006. Therefore, if regional production is dominated by these sectors at the beginning of the study period, then there will be a poor endogenous growth performance, because this will be likely to have been dominated by what has happened in those sectors at the national level. It is also evident from Table 14.3 that an increase in the LQ for manufacturing industries employment over the period 1996–2006 (LQ_MAN_CH) will have a negative impact on endogenous regional growth performance.

14.5.2.6 R1: Industry Specialization and Structural Change Measures

This factor is composed for two measures of industry specialization in a region, a structural change index (SCI) and a Herfindahl-Hirschman specialization index (SPEC_96). As shown in Table 14.3 it is evident that the higher the specialization at the beginning of the period 1996–2006 (SPEC_96) the lower the endogenous regional growth performance across a FER for that decade. That is an expected result because specialization of the region will be more dependent on what

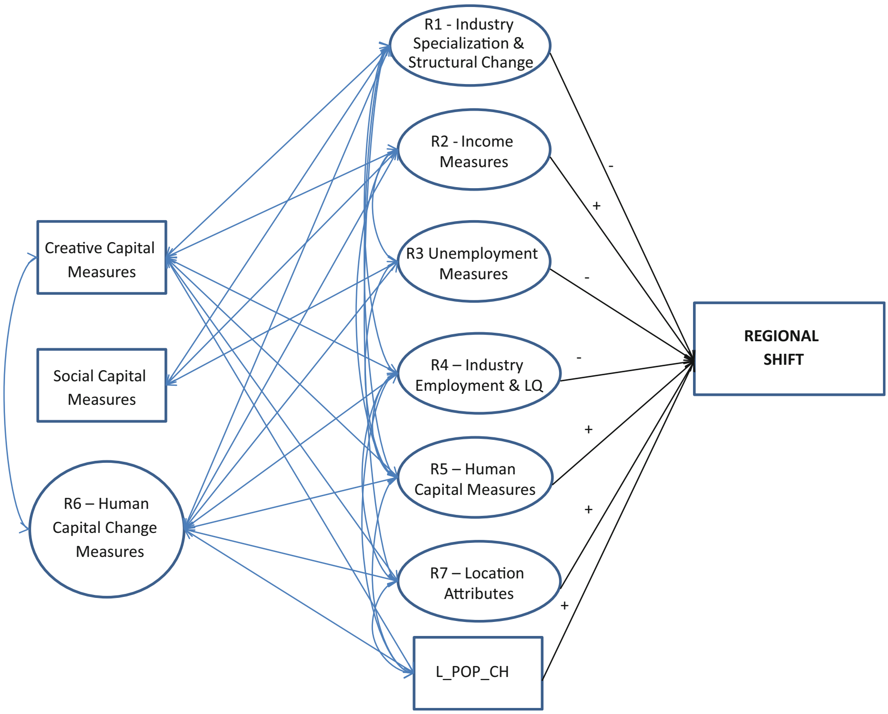

Fig. 14.3 The estimated structural model (Source: The Authors)

happened in that sector at national level. Thus, it is likely that the more diversified an economy at the regional level the larger the endogenous regional growth.

14.5.2.7 R3: Unemployment Measures

This factor is less important in terms of its explanatory power in the model compared to factors R4 and R3 among those that have a negative impact on endogenous regional growth dependent variable (REG_SHIFT). The negative impact is based on the initial level of unemployment (UNEMP_96) and also on the change in this variable (UNEMP_CH). The result is interesting because the larger the initial level of unemployment the larger the endogenous growth will be, probably because there is more room for the expansion of the economy at the regional level. However, if the unemployment increases over the period 1996–2006 there will be a poor endogenous growth performance in a region.

We now turn to the left hand panel in Fig. 14.3 which indicates the relationships between on the one hand the creative capital measure (CREATIVE_06) and the social capital measure (VOLUNTEER_06) as variables and factor R6, the human capital change measures, and on the other hand and the R1, R2, R3, R4, R5 and R7

Table 14.4 Correlation estimation in the final model

Covariances			Estimate	S.E.	C.R.	P	Correlations
R2	< − >	R3	−.001	.000	−4.564	***	−.491
R1	< − >	R5	.000	.000	−4.063	***	−.365
R1	< − >	R7	−.012	.002	−5.552	***	−.617
R5	< − >	R7	.001	.001	5.473	***	.588
R2	< − >	R5	.000	.000	−4.504	***	−.244
R3	< − >	R5	.000	.000	4.029	***	.175
R4	< − >	R5	.001	.000	7.175	***	.857
R1	< − >	R4	−.012	.002	−6.005	***	−.657
R4	< − >	R7	.094	.014	6.595	***	.855
R6	< − >	R7	.000	.000	−4.587	***	−.505
R6	< − >	R5	.000	.000	−6.613	***	−.952
R6	< − >	R1	.000	.000	3.102	.002	.275
R6	< − >	R2	.000	.000	4.253	***	.303
R6	< − >	R3	.000	.000	−3.802	***	−.212
R6	< − >	R4	.000	.000	−5.963	***	−.769
L_POP_CH	< − >	R4	.004	.001	3.105	.002	.222
L_POP_CH	< − >	R6	.000	.000	−2.567	.010	−.211
L_POP_CH	< − >	R7	.006	.001	4.302	***	.366
L_POP_CH	< − >	R5	.000	.000	2.382	.017	.185
VOLUNTEER_06	< − >	R3	.001	.000	3.216	.001	.220
VOLUNTEER_06	< − >	R2	.001	.000	2.789	.005	.215
VOLUNTEER_06	< − >	R1	−.002	.000	−5.967	***	−.483
CREATIVE_06	< − >	R4	.005	.001	6.868	***	.733
CREATIVE_06	< − >	R2	.000	.000	−2.359	.018	−.125
CREATIVE_06	< − >	R1	−.001	.000	−5.877	***	−.561
CREATIVE_06	< − >	R5	.000	.000	6.229	***	.597
CREATIVE_06	< − >	R7	.005	.001	5.948	***	.637
CREATIVE_06	< − >	R6	.000	.000	−5.490	***	−.585
CREATIVE_06	< − >	L_POP_CH	.000	.000	4.095	***	.310

Source: The Authors

factors and the variable L_POP_CH. Referring back to Table 14.4, we see that all the covariances for all the factors and variables in the table are significant at a level lower than $p = 0.05$ (that is because the search process in structural equation modelling has specifically eliminated those that are non-significant and thus are not influencing the variability in the endogenous regional growth performance of the dependent variable REG_SHIFT).

What we thus see from Table 14.4 is the following:

(a) Taking first the creative capital variable (CREATIVE_06), there is a positive relationship with all the factors and the variable except with the specialization factor (R1) and with the income factor (R2) with which there is a negative association. And there is not a significant association with the unemployment factor (R3). Thus, the level of the incidence of employment in the creative capital industries in a region is positively related to metropolitan and urban location attributes, human capital availability and with industry employment (LQ measures) – as might be expected – while it is negatively related to income.

(b) Next, taking the social capital measure (VOLUNTEER_06), there is a positive relation with income (R2) and unemployment (R3). Thus, volunteering as a measure of social capital is likely to be higher when associated with higher regional income and also when unemployment is higher. This may seem contradictory but that is not necessarily so because it indicates that both good and not so good economic conditions may be associated with this aspect of social capital, with higher income enhancing volunteering and spare time associated with unemployment also enhancing it. It is also evident that social capital as measured by volunteering is less associated with a higher incidence of specialization (factor R1).

(c) Finally, the change in human capital measure (factor R6) is significantly related to all of the factors, positively factors R1 (specialization) and R2 (income) and negatively related to unemployment measures (R3), human capital measures (R5), and location attributes (R7) Thus on the one hand the change in human capital is higher in more specialized and higher income regions, while on the other hand the change in human capital is lower in regions with higher unemployment, higher initial human capital, and in metropolitan and urban regions.

14.6 Comparing the Structural Equation Modelling and the OLS Regression Modelling Results

We now turn to compare the results from the OLS regression modelling approach used in the Stimson et al. (2009a, b, 2010) analysis with those of the structural equation modelling approach discussed in this chapter. The findings from both of these modelling approaches are summarized in Table 14.5. In the columns in the left hand side of the table the results from the OLS general model, the OLS specific model (derived from a backward step-wise regression model), and a spatial error and a spatial lag model are given. In the right hand side of the table the results of the structural equation model are given.

As was described previously, the estimates of the structural model are the coefficients measuring the impact of the factors (R1 to R7) on the dependent variable REG_SHIFT. The sign for all of them are as expected as was explaining in the previous section. When we compare the results with the ones obtained by the Stimson et al. (2009a, b, 2010) OLS modelling approach some significant differences arises.

There are two significant pieces of information from the structural equation modelling results that are not provided by the results of the OLS modelling approach:

(a) The first is that the composition of the factors provides a clearer interpretation and they have larger significance. This is the case for all the factors, and there

Table 14.5 Comparing the OLS regression and the structural equation modelling

Dependent variable: REG_SHIFT								
	OLS and spatial regression modeling				*Structural equation modeling (SEM)*			
					Structural model – standarized factors			
						Measurement model		
Expalnatory variables	OLS general model results	OLS specific linear model	Spatial error model	Spatial lag mode	*Factor*	*Estimate*[a]	*Factor Load*	*Factor Name*
Intercept	0.5430	1.1480	−0.0217	0.9583				
SCI	−1.1660	−1.3240	−1.1129	−1.3799	R1	−0.730	0.815	R1-Industry specialization and structural change measures
SPEC_96	0.0500						0.721	
SPEC_CH	0.4670	0.4230	0.3628					
SCI_CH	1.2350	1.3060	1.2317	1.4811				
L_INC_CH	0.2370		0.4333		R2	0.266	0.776	R2 – Income measures
L_INC_96	−0.1730	−0.3920		−0.3630			−0.879	
UNEMP_CH	−2.4210	−2.4320	−2.0998	−2.4721	R3	−0.329	0.924	R3 – Unemployment measures
UNEMP_96	−1.2610	−1.3850	−1.0275	−1.2331			−1,026	
LQ_PRO_96	0.0770	0.0690	0.0684		R4	−1.597	0.930	R4 – Industry employment and location quotient measures
LQ_FIN_96	−0.0050						0.906	
LQ_INF_96	−0.0140						0.885	
LQ_MAN_96	0.0200			0.0407			0.388	
LQ_MAN_CH	0.0620	0.0670		0.0774			−0.359	
LQ_INF_CH	0.0170						0.199	
LQ_FIN_CH	−0.0550						0.195	
LQ_PRO_CH	0.0980	0.1160	0.1419					

POSTGRAD_96	−5.9040	−5.3680	−6.4220		R5	0.817	0.919	R5 – Human capital measures
BACHELOR_96	1.3690						1,008	
TECHQUALS_96	−0.8960	−0.5220	−0.7994				0.46	
POSTGRAD_CH	−1.3580				R6			R6 – Human capital changes measures
BACHELOR_CH	2.7740							
TECHQUALS_CH	0.8240	1.3280	1.0358	1.7195				
A_COAST	0.0060				R7	0.585	0.253	R7 – Location attributes
P_METRO	−0.0080						0.800	
D_URBAN	0.0070						0.870	
D_REMOTE	−0.0100						−0.584	
L_POP_CH	2.3170	2.3920	2.3525	2.5635	L_POP_CH	0.632		
VOLUNTEER_06	0.5730	0.5710	0.5446	0.6418				
CREATIVE_06	1.1520	1.0990	0.7912	0.6821				
SYMBA_96	−0.0290							
SYMBA_CH	−0.1330	−0.1190	−0.1400					
L_POP_96	−0.0130							

[a]The estimated factors in the Structural Model are associated with the factor loading in the Measurement Model

Source: Stimson et al. (2009a, b, 2010) for the OLS and spatial regression modelling; the authors for the structural equation modelling are some that help to clarify the OLS results. For example, the income measure factor is formed by two variables: log of the level of income in 1996 (L_INC_96); and the change in this variable over time (L_INC_CH). While in the OLS Specific Linear Model and the Spatial Lag Model the initial level of income is the significant variable with a negative sign, in the Spatial Error Model the significant variable is the change in income with positive sign. What the structural equation model results tell us is that there is a high communality in the variance of those two variables, and they affect the dependent variable (REG_SHIFT) in different directions. Both results are compressed in factor 2 and are explained in the loading that forms this factor.

(b) A second result that is important is the one associated with the Human Capital measures. While the levels of these variables have a negative sign in OLS regression modelling – which is hard to explain – the change is that one of the variables has a positive sign. But in the structural equation modelling the results are clear and unambiguous, and indicate that Human Capital has a strong effect on endogenous growth, and the change over time is not significant. In addition, when we look at the correlation among these two factors we see that they are highly and negative correlated, which means that the higher the human capital in a region the lower the change. In this context, factor 7, the Location Attributes come out with the right sign and provide a clear explanation for the loading that makes sense and is consistent with endogenous growth theory.

14.7 Conclusion

In this chapter we have experimented with a structural equation modelling approach to investigate the potential determinants of spatial variation in the performance of FERs in Australia over the decade 1996–2006 on a measure of endogenous regional employment that relates to the regional shift component derived from a shift-share analysis using a methodology proposed by Stimson et al. (2005) and Stimson and Stough (2009b). The objective was to examine and demonstrate the potential advantage of a structural equation modelling approach over the more traditional OLS regression modelling approach used by Stimson et al. (2009a, b, 2010) using the FER same data set. What the results show is that the structural equation model approach has an advantage whereby the composition of the explanatory factors provides a clearer interpretation than was the case in the OLS regression model, and they have larger and stronger significance. In addition the signs of the factors appear to better conform to those offered by theory on endogenous regional development. Intuitively the results derived from the structural equation model approach presented in this chapter appear to provide an overall more satisfactory and insightful understanding of the factors that might underpin the explanation of what causes spatial variation in the endogenous employment performance of FERs across Australia over the decade 1996–2006.

The structural equation modelling approach seems to have the advantage of helping us to address the measurement (endogeneity) problem and the multi-collinearity problem inherent in the OLS regression modelling approach that is common in spatial econometric analysis in regional science. Its wider adoption may be an important methodological advance in spatial econometric analysis of regional economic performance across regions within nations. Certainly the results from the exploratory application of the structural equation modelling approach applied to the EFRs data set for Australia seem to point in that direction. But it will be important for comparisons to be made of the results derived from the structural equation modelling approach *vis-à-vis* the OLS regression modelling approach using data sets for other countries in order to validate the claims of methodological superiority that seem to be evident from the initial experiment we have run on the Australian data reported in this chapter.

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References

Amin A, Thrift N (1995) Globalisation, institutional "thickness" and the local economy. In: Healey P, Cameron PS, Davaoudi S, Graham S, Madani-Pour A (eds) Managing cities: the new urban context. Wiley, Chichester/New York, pp 92–108

Anselin L (1988a) Spatial econometrics: methods and models. Kluwer, London

Anselin L (1988b) Model validation in spatial econometrics: a review and evaluation of alternative approaches. Int Reg Sci Rev 11:279–316

Arrow KJ (1962) The economic implications of learning by doing. Rev Econ Stud 29:155–173

Arthur WB (1994) Increasing returns and path dependency in the economy. University of Michigan Press, Ann Arbor

Barro RJ (1990) Government spending in a simple model of endogenous growth. J Polit Econ 98: S103–S125

Barros R, Broadbent RA, Cordey-Hayes M, Massey DB, Robinson K, Willis J (1971) An operational urban development model for Cheshire. Environ Plan 3:115–234

Bentley J (2002) New wines in old bottles: the challenge of developing leaders. In: Derr B, Rousillon S, Bournois F (eds) Latin America. Cross cultural approaches to leadership development. Quorum, Westport

Bollen KA, Bauer DJ, Christ SL (2010) Overview of structural equation modeling. In: Kolenikov S, Steinley D, Thombs L (eds) Statistics in the social sciences. Wiley, New York, pp 37–78

Bolton R (1992) 'Place prosperity' vs 'people prosperity'. Urban Stud 29:185–203

Bolton R (1999) Place surplus, exit, voice, and loyalty. Uddevalla symposium on evaluation of regional policies, Fiskebackkil, June

Brooklym C, Bousillon S, Bournois F (eds) (2002) Cross-cultural approaches to leadership. Quorum/Greenwood, Westport

Byrne B (2010) Structural equation modeling with AMOS: basic concepts, applications, and programming, 2nd edn. Routledge, London

Castells M, Hall P (1994) Technopoles of the world: the making of 21st century industrial complexes. Routledge, London
Capello R, Nijkamp PJ (eds) (2009) Regional growth and development theories in the XXI century: theoretical achievements and future challenges. Edward Elgar, Cheltenham
Clingermayer JC, Feiock RC (2001) Institutional constraints and policy choice: an exploration of local government. State University of New York Press, New York
Coleman J (1988) Social capital in the creation of social capital. Am J Sociol 94:95–120
de Santis M, Stough RR (1999) Fast adjusting urban regions, leadership and regional economic development. Reg et Dev 10:37–56
Doig J, Hargrove E (1987) Leadership and innovation: a biographical perspective on entrepreneurs in government. John Hopkins University Press, Baltimore
Duranton G, Puga D (2000) Diversity and specialization in cities: why, where and when does it matter. Urban Stud 37:533–555
Erickson RA (1994) Technology, industrial restructuring and regional development. Growth Change 25:353–379
Erickson RA, Leinbach T (1979) Characteristics of branch plants attracted to non metropolitan areas. In: Lonsdale R, Seyter HL (eds) Non metropolitan industrialisation. Winston, Washington, DC
Fainstein S (1983) Restructuring the city: the political economy of urban redevelopment. Longman, New York
Fairholm GW (1994) Leadership and the culture of trust. Praeger, Westport
Florida R (1995) Toward the learning region. Futures 27:527–537
Florida R (2002) The rise of the creative class; and how it's transforming work, leisure, and everyday life. Basic Books, New York
Goetz SJ, Rapasingla A (2001) The returns to higher education: estimates for the contiguous states. Paper to Regional Science Association international, North American annual meeting, Charleston, November
Gordon IR, McCann P (2000) Industrial clusters, complexes, agglomeration and/or social networks. Urban Stud 373:513–532
Greene WH (2002) Econometric analysis, 5th edn. Prentice Hall, Upper Saddle River
Grossman GM, Helpman E (1991) Innovation and growth in the global economy. MIT Press, Cambridge, MA
Hanushek EA, Kimko DD (2000) Schooling, labour-force quality, and the growth of nations. Am Econ Rev 90:1184–1208
Heenan DA, Bennis WG (1999) Co-leaders: the power of great partnerships. Wiley, New York
Hofstede G (ed) (1997) Cultures and organization: software of the mind. McGraw-Hill, New York
Henderson JV, Kuncoro A, Turner M (1995) Industrial development in cities. J Polit Econ 103:1067–1090
Huxam C (1996) Collaborative advantage. Sage, Thousand Oaks
Jessop B (1998) The narrative of enterprise and the enterprise of narrative: place marketing and the entrepreneurial city. In: Hubbard T, Hall PH (eds) The entrepreneurial city. Wiley, Chichester/New York, pp 77–99
Jin DJ, Stough RR (1998) Learning and learning capability in the Fordist and post-Fordist age: an integrative framework. Environ Plan A 30:1255–1278
Johansson B, Karlsson C, Stough RR (eds) (2001) Theories of endogenous regional growth. Springer, Berlin
Kaplan D (2009) Structural equation modeling: foundations and extensions, 2nd edn, Advanced quantitative techniques in the social sciences series. Sage, Los Angeles
Kaufman R (1993) An empirical exploration of the relation among diversity, stability and performance in economic systems. Struct Change Econ Dyn 4:299–313
Kirzner IM (1973) Competition and entrepreneurship. The University of Chicago Press, Chicago
Kline RB (2005) Principles and practice of structural equation modeling, 2nd edn. Guilford, New York

Krugman P (1991) Geography and trade. MIT Press, Cambridge, MA
Lande P (1994) Regional industrial structure and economic growth and stability. J Reg Sci 34:343–360
Lucas R (1985) Models of business cycles. Basil Blackwell, Oxford
Lucas RE (1988) On the mechanics of economic development. J Monet Econ 22:3–42
Maier G (2001) History, spatial structure, and regional growth: lessons for policy making. In: Johansson B, Karlsson C, Stough RR (eds) Theories of endogenous regional growth. Springer, Heidelberg, pp 255–277
Maillat D, Kibir L (2001) The learning region and territorial production systems. In: Johansson B, Karlsson C, Stough RR (eds) Theories of endogenous regional growth. Springer, Heidelberg, pp 255–277
Malecki E (1991) Technology and economic development: the dynamics of local, regional and national competitiveness. Longman Scientific and Technical, Harlow
Malecki E (1998a) How development occurs: local knowledge, social capital, and institutional embeddedness. Paper presented at the annual meeting of the Southern Regional Science Association. Savannah
Malecki E (1998b) Technology and economic development: the dynamics of local, regional and national competitiveness. Paper presented to the annual meeting of Southern Regional Science Association, Savannah
Markusen A (1985) Profit cycles, oligopoly and regional development. MIT Press, Cambridge, MA
Masser I, Brown PJB (1975) Hierarchical aggregation procedures for interaction data. Environ Plan A 7:509–523
Masser I, Scheurwater J (1980) Functional regionalisation of spatial interaction data: an evaluation of some suggested strategies. Environ Plan A 12:1357–1382
Mitchell WF, Flanagan M (2009) The CofFEE functional economic regions: first edition. Centre of Full Employment and Equity, Newcastle
Norton RD, Rees J (1979) The product cycle and the decentralization of North American manufacturing. Reg Stud 13:141–151
North D (1990) Institutions, institutional change and economic performance. Cambridge University Press, Cambridge
OECD (2000) Learning regions and cities: knowledge, learning and regional innovation systems. Organization for Economic Cooperation and Development, Paris
Oud JHL, Folmer H (2008) A structural equation approach to models with spatial dependence. Geogr Anal 40:152–166
Parkinson M (1990) Leadership and regeneration in liverpool: confusion, confrontation, or coalition, in Houston. In: Judd and Parkinson (1990), pp 241–257
Patten C (1991) The competitiveness of small firms. Cambridge University Press, Cambridge
Pollitt C, Bouckaert G (2002) Public management reform: a comparative analysis. Oxford University Press, Oxford
Porter ME (1985) Competitive advantage: creating and sustaining superior performance. Free Press, New York
Porter ME (1986) Competition in global industries. Harvard Business School Press, Cambridge, MA
Porter ME (1990) The competitive advantage of nations. MacMillan, New York
Putnam R (1993) The prosperous community: social capital and public life. Am Prospect 13(Spring):35–42
Rebelo S (1991) Long run policy analysis and long run growth. J Polit Econ 98:S71–S102
Rees J (1979) State technology programs and industry experience in the USA. Rev Urban Reg Dev Stud 3:39–59
Rees J (2001) Technology and regional development: theory revisited. In: Johansson B, Karlsson C, Stough RR (eds) Theories of endogenous regional growth. Springer, Heidelberg, pp 94–110
Rodrick D (1998) TFPG Controversies, institutions and economic performance in Asia. The institutional foundations of East Asian economic development. In: Hayami Y, Aoki M (eds) Proceeding of the IEA conference held in Tokyo, Japan. St. Martin Press in association with the International Economic Association, New York

Romer PM (1986) Increasing returns and long-run growth. J Polit Econ 94:1002–1037

Romer PM (1990) Endogenous technological change. J Polit Econ 98:S71–S102

Saxenian A (1994) Regional advantage: culture and competition in silicon valley and route 128. Harvard University Press, Cambridge, MA

Schumpeter JA (1934) The theory of economic development. Harvard University Press, Cambridge, MA

Scott AJ (1988) New institutional spaces: flexible production organization and regional development in North American and Western Europe. Pion, London

Simmie J (ed) (1997) Network and learning regions. Jessica Kingsley, London

Smilor RW, Wakelin M (1990) Smart infrastructure and economic development: the role of technology and global networks. In: Kozmetzky G, Smilor RW (eds) The technopolis phenomenon. IC2 Institute, University of Texas, Austin, pp 53–75

Shyy T-K, Song C, Stimson RJ, Stough RR (2009) Differentials in endogenous regional employment growth in U.S. metropolitan areas: the explanatory role of entrepreneurship and other leadership and institutional factors. In: Bernhard I (ed) The geography of innovation and entrepreneurship. Revised papers presented at the 12th Uddevalla symposium, Baari, Italy, 11–13 June 2009, Research reports 2009: 02, University West, Trollhattan, Sweden, pp 921–950

Stimson RJ, Robson A, Shyy T-K (2009a) Measuring regional endogenous growth, Ch. 18. In: Capello R, Nijkamp PJ (eds) Handbook of regional growth and development theories. Edward Elgar, Cheltenham, pp 354–372

Stimson RJ, Robson A, Shyy T-K (2009b) Modelling regional endogenous growth: an application to the non-metropolitan regions of Australia. Ann Reg Sci 43:379–398

Stimson RJ, Rohde D, Shyy T-K, Mitchell W (2010) Using functional economic regions to model aspects of regional performance in Australia. Paper delivered to the Tinbergen Institute International Workshop 2010, modelling innovation, entrepreneurship and regional development, Amsterdam, 17–18 May

Stimson RJ, Stough RR, Salazar M (2005) Leadership and institutional factors in endogenous regional economic development. Investig Reg 7:23–52

Stimson RJ, Stough RR (2009a) Regional economic development: methodology and analysis. In: Rowe JE (ed) Theories of local economic development: linking theory to practice. Ashgate, Farnham, pp 169–192

Stimson RJ, Stough RR (2009b) Leadership, institutions and regional endogenous development. Edward Elgar, Cheltenham

Stimson RJ, Stough RR, Nijkamp P (eds) (2011) Endogenous regional development: perspectives, measurement and empirical investigation. Edward Elgar, Cheltenham

Stimson R, Stough R, Roberts B (2006) Regional economic development: analysis and planning strategy. Springer, Berlin

Taylor PJ, Catalano G, Gane N (2002) A geography of global change: services and cities 2000–01, GaWC Research Bulletin, Globalisation and World Cities Study Group and Network, 77, pp. 1–9.

Thomas MD (1975) Growth pole theory, technological change and regional economic growth. Pap Reg Sci Assoc 34:3–25

Vasquez-Barquero BA (2002) Endogenous development: networking, innovation, institutions and cities. Routledge, London

Ward JH (1963) Hierarchical grouping to optimize an objective function. J Am Stat Assoc 58:236–244