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Francesco Pastore *Editors*

Geographical Labor Market Imbalances

Recent Explanations and Cures

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Acknowledgements

This edited book is a collection of some of the most remarkable contributions dealing with regional issues and presented at the XXVII AIEL (Italian Association of Labor Economists) Conference held at University of Naples II, at the Faculty of Law in Santa Maria Capua Vetere and in the magnificent scenario of the Royal Palace of Caserta on the 27th and 28th of September 2012.

It is the eighth volume in the AIEL series published with Springer Verlag. Like all the other volumes in the series, it will be indexed in a number of important bibliographic repositories, such as, among others, ISI Web of Knowledge, Scupus, Ebsco, IDEAS/RePEc. This guarantees that also this book, similar to other books in the series, will represent an important outlet for the scholars who have contributed to it. It is important to notice that each chapter included in the volumes within the AIEL series has recorded a large and increasing number of downloads and citations. Some volumes reach for instance about 1,000 downloads per year. This popularity is also a sign of the quality and effort that the editors of the books in the series have traditionally put in making this product of the highest quality in its type, as shown, for instance, by the selection and refereeing process implemented in preparing the volume.

This volume is no exception under this respect. Every chapter of this book has been first of all selected among a number of possible candidates. In addition, it has undergone a double blind refereeing process, involving in addition to one internal referee, essentially one of the editors, also from one to three external referees. We feel greatly indebted to all of them for their generosity, wisdom, and competence. Below is the full list of referees who have contributed with their valuable work to publishing a better volume.

We are proud to notice that researchers coming from seven different countries have contributed to this collective effort. In addition, 8 out of 26 referees, including the editors, are non-Italians. This confirms the international dimension of labor market research in Italy and in particular of the AIEL conference. As it is possible to check in the renewed and dynamical Web site of the association, an increasing number of conference participants are from abroad.

Importantly, this book would have not been possible without the financial support of a number of institutions. First is the Italian Association of Labor Economists. We wish to especially thank the two Presidents of the Associations during the period of preparation of the book, namely Sergio Pietro Destefanis and Claudio Lucifora. We wish also to thank all the executive board of the association, which includes in addition to one of the editors, Francesco Pastore, also Elisabetta Addis, Donata Favaro, Marco Leonardi, Paolo Naticchioni, and Dario Sciulli. Second, we wish to thank the departments where we work, which have also contributed in various ways to the publication of the book, namely the Department of Law of *Seconda Università di Napoli* and the Departments of Economic and Social Sciences of the *Università Cattolica del Sacro Cuore (Piacenza)*.

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Chapter 1
Introduction

Chiara Mussida and Francesco Pastore

Abstract This introductory chapter presents the book concept and tries to draw the red line which connects its various parts. It does so by means of a presentation of the main content of each chapter of the book, which is located in the relevant literature in order to allow the reader to better appreciate the main novelties.

Keywords Agglomeration • Factor mobility • Industrial change • Industrial concentration • Regional inequality • Regional convergence

JEL Classification C33, E24, J63, P52, R23

Until recently, labor mobility and wage flexibility were at the core of the debate over the causes and effects of territorial labor market imbalances. In a typical neoclassical model, slow-growth, high-unemployment regions are characterized by supply-side constraints and institutional rigidities. However, such explanations leave largely unanswered the questions of how territorial differences in productivity levels and unemployment rates arise in the first place and why territorial differences in labor market performance are persistent over time. Unemployment divergence or unemployment club convergence have been noted in a large literature and recently studied also using spatial econometric analysis.

In this book we aim to develop the debate on such important new topics as:

– The reasons why structural change in some sectors causes a slump in some regions but not in others.
– The extent to which agglomeration factors explain regional imbalances.
– The degree of convergence/divergence across EU countries and regions.

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– The role of labor mobility in reducing/increasing regional labor market imbalances.
– The impact of EU and country-level regional policy in stimulating convergence.
– The (unsatisfactory) role of active labor market policies in stimulating labor supply in the weakest economic areas.

This book comprises 16 chapters structured in 4 parts. The four chapters in Part I provide a general overview of the determinants of regional unemployment, by looking, respectively, at the role of structural change, the static and dynamical determinants within the context of panel data analysis, the role of compensating wage differentials, and the factors leading to convergence in unemployment rates in the long run.

Neoclassical theories mainly point to wage flexibility and the ensuing mobility of production factors as means of adjustment and convergence. Within this approach, whatever the reason of the emergence of regional unemployment differentials, the best way to get rid of them is by facilitating factors mobility. If labor moves from high to low-unemployment regions, the local unemployment rates will equalize in the two areas. Elhorst (2003), Ferragina and Pastore (2008), and Pastore (2012) provide more recent and articulate surveys of the literature.

It is a common belief, based on Blanchard and Katz (1992), that the quick convergence achieved by the states within the United States of America is achieved thanks to much greater migration flows and flows that are more sensitive to geographical unemployment differences. The ensuing studies based on Blanchard and Katz (1992) invariably found that labor migration was much lower in Europe and less sensitive to local labor market conditions, for a number of reasons, such as language differences, rigidity in the labor market, and strong qualification systems that reduce the returns to migration for the best qualified workers in high-unemployment areas. Recent research by Beyer and Smets (2014) shows that this situation is slowly changing in the sense that European countries are crossed by much bigger migration flows, although not as big as in the United States and much more sensitive to the evolution of unemployment differentials. This is likely to increase the speed of adjustment to external shocks and, therefore, accelerate convergence in the years to come. Nonetheless, still now, regional migration flows are considered as only one of the channels of regional unemployment convergence in Europe. Migration from high to low-unemployment regions may cause unemployment differentials to equalize in the short run, but if the factors causing the emergence of regional unemployment differentials are not addressed directly, there might be no convergence in the long run. In some European countries, such as France, Belgium, and Spain, the highest regional unemployment rates were approximately twice as the lowest. In Italy, the regional heterogeneity in terms of unemployment rates is even higher, and it has increased since 2008 (Marelli et al. 2012). The persistent differences in unemployment rates across countries, within countries, and across regions have put the role of migration and labor mobility adjustment back on the European policy agenda.

The first part of the chapter by Chiara Mussida and Francesco Pastore provides also an overview of the existing literature on regional unemployment differentials, while the chapter by Semerikova provides an empirical context within the field of panel data analysis to understand the determinants of local unemployment.

The latter includes the greater turbulence of labor markets in high-unemployment regions of Italy, documented by Mussida and Pastore and other previous studies on Italy, such as Basile et al. (2012), as well as a number of other countries, such as Poland (Newell and Pastore 2006; Pastore and Tyrowicz 2012) and Spain (Hernanz and Izquierdo 2014). Mussida and Pastore provide a new empirical exercise based on the use of the longitudinal file of the Italian labor force survey gathered by the Italian National Institute of Statistics (ISTAT) over the period 2004–2010. It is only recently that this important longitudinal dataset has been made available to researchers so as to allow studying the geographical distribution of labor market flows. The authors show that high-unemployment regions have a higher degree of worker turnover than low-unemployment regions. Moreover, worker turnover correlates positively across regions with the degree of industrial change as measured by the Lilien index, and negatively with the degree of industrial concentration as measured by the Herfindahl index.[1] These findings suggest that a high degree of turbulence makes it harder for firms and jobs which are generated in the Italian Mezzogiorno to survive. This implies that also jobs tend to be lost more easily in the South, which contributes to higher local unemployment. More specifically, the findings hint that sectoral shifts and industrial concentration might explain a variation of between 25 and 40 % of the gap in worker turnover rates across regions. This general conclusion is robust to the use of different control variables and suggests that policy aimed at preventing the destruction of jobs in Southern regions would be important.

In her chapter, Elena Semerikova investigates the determinants of regional unemployment differentials in Germany in a spatial panel data context. She implements an up-to-date, rigorous enquiry based on all the typical controls not only for static but also for dynamic panel data analysis, such as system GMM and spatial ML estimation. The study is carried out at a fine level of aggregation, involving almost all of the 413 NUTS III localities, over the period from 2001 to 2009. Her findings confirm the role of traditional determinants of regional unemployment differentials. In particular, her study confirms that the factors which tend to increase regional unemployment differentials include the cost of labor, the share of workers employed in agriculture and construction, the share of young workers, and that of workers with low professional qualifications. Other less traditional factors that reduce regional unemployment differentials include employment growth, the share of workers employed in manufacturing, local GDP, population density, and the degree of attractiveness. The dynamic model also allows capturing the important role of indirect effects, namely the effects that come to some regions from neighboring regions. The fact that such effects are caught only in the dynamic model implies

[1]This research has also led to the elaboration of a new routine in STATA for computing the Lilien index (Ansari et al. 2014).

that they affect the other regions with some time lag. Interestingly, the indirect effects are even stronger than the direct effects. Analyzing the magnitude of the spatial dependence between regions allows her assessing the role of labor mobility in labor market disparities. The study reveals significant spatial dependence between unemployment rates as well as exploratory characteristics of the regions, which might be an indication of high importance of labor mobility for regional unemployment rates.

The study also makes an attempt to explore differences in spillover effects between different parts of the country. Applying a special extended specification developed by Demidova et al. (2013) allows her analyzing the spillover effects not only within Eastern and Western regions of Germany, as it was done by Lottmann (2012), but also between Western and Eastern local areas. It appears that the unemployment rate of the Eastern regions influences both the unemployment in the West part and in the East part of Germany, whereas the unemployment of Western regions affects only its own unemployment. The author concludes that unemployment in West Germany seems to be more of disequilibrium nature, and the unemployment in East Germany is more of equilibrium nature. The disequilibrium view assumes that unemployment rate reaches its underlying mean only in the long-run period since the adjustment can be sluggish. Hence, differences in unemployment rates will not vanish also over a long period of time. The equilibrium view assumes that external shocks or economic disturbances in the labor market affect the unemployment rate for a short period of time, allowing it to converge back to its mean value. According to this approach, each region has its own underlying mean unemployment rate in the stable equilibrium.

In his chapter, Aleksey Oshchepkov analyzes cross-regional wage differentials in one of the largest countries in the world, Russia. He argues that these differentials may be understood within the compensating differences framework. In other words, Russian workers receive wage compensations for living in regions with a higher price level and worse nonpecuniary characteristics, and these wage compensations constitute more than 50 % of total cross-regional wage differentiation. Moreover, regional amenities and disamenities explain much more variation than differences in employment composition. In this regard, the Russian case seems to be specific and interesting not only among other transition countries but also in the European perspective, as most existing studies are silent about compensating mechanisms and exploit only the labor demand side of the "story." An important policy implication of the study is that the best policy reaction to the observed high level of interregional wage differentials should be the removal of migration barriers and a reduction in migration costs. This would contribute to the growth in the level of wage compensations for workers living in regions with relatively unfavorable living conditions. Welfare growth could be achieved in this case even in spite of a possible rise in the differentials in nominal wages.

The study makes some methodological contributions to the literature on assessing empirically the role of compensating wage differentials: first, it explicitly takes into account migration costs and living costs; second, it proposes instrumental variables to overcome the problem of endogeneity of regional characteristics; and third, it estimates the extent to which the observed wage differentiation may be considered as compensative.

The chapter by Alisher Aldashev analyzes convergence of wages in Kazakhstan using a panel of regions (NUTS3 level). The rate of convergence in monthly wages has been estimated using a nonlinear least squares model similar to Barro and Sala-i-Martin (1991). To allow for the possibility of a structural break, the rate of convergence was estimated separately for the period before the world financial crisis (2003–2007) and the period after it (2008–2011). Given that regions interact with one another (e.g., because of migration), spatial correlation poses an econometric problem. To correct for spatial correlation, the author constructs the artificial regression and apply the method by Driscoll and Kraay (1998) for spatial panels. He also finds an indication that before the crisis, the oil-rich regions had higher steady-state growth rates which is in contrast to cross-country analyses in the literature suggesting that resource-abundant countries experience slower growth. His findings also suggest that spending on research and development is an important factor contributing to growth. This implies, in turn, that investment in R&D might help achieve higher growth rates which might be of great importance for regions which experience slow growth.

Part II and III are probably the newest ones, at least in terms of the novelty of the issues dealt with, such as the role of agglomeration factors, of R&D, of foreign direct investment, and of human capital accumulation. Part II focuses, more specifically, on agglomeration economies and is, therefore, based on the New Economic Geography approach to regional economic development and, indirectly, labor market imbalances. Direct predictions regarding regional unemployment differentials within the context of the NEG have been produced in, among others, Epifani and Gancia (2005) and Francis (2009). The most recent explanations of regional unemployment resort to agglomeration economies as factors able to explain regional unemployment differentials by means of greater advantages of the already most developed areas of a country.

Following the broad literature started by Glaeser et al. (1992) and Henderson et al. (1995),[2] in their chapter, Roberto Basile, Cristiana Donati, and Rosanna Pittiglio analyze the effect of many factors, i.e., the presence of an industrial district, the level of productive specialization, the degree of sectoral diversification, the population density, the level of local competition, and the average firm size, characterizing the local industry structure on employment growth in Italy. They claim that the results of previous studies on the Italian case (i.e., Mameli et al. 2008; Paci and Usai 2008; Cainelli and Leoncini 1999) suffer from a number of model misspecifications, connected to the measurement of Marshallian externalities, to the specification of the functional form of the model, and to the presence of unobserved spatial heterogeneity. Using census data for 686 Local Labor Systems (LLS) in Italy

[2]See also, i.e., Henderson (1997), Combes (2000), Rosenthal and Strange (2004), de Groot et al. (2009), Melo et al. (2009). For a recent review of the literature, see Beaudry and Shiffauerova (2009).

for three different periods (1981–1991, 1991–2001, and 2001–2008), the authors contribute to existing literature by using a semiparametric model which allows them to identify smooth nonlinear effects of the growth predictors, to link the effect of industrial districts and to control for spatial unobserved heterogeneity. Empirical findings confirm that industrial districts have performed better than the other LLSs during the sample period. Regression results also highlight a nonlinear relationship between specialization and local employment growth: net of the industrial districts' effect, a higher specialization increases productivity and reduces, under the assumption of inelastic product demand, labor demand. However, after a certain threshold, location economies exhaust their effect on productivity and, thus, on employment therefore generating a nonlinear relationship between specialization and employment growth. In line with previous evidence and corroborating Jacobs' theory, diversification boosts employment growth in manufacturing and reduces it in services. Allowing for nonlinearities and in keeping with theoretical predictions, they find a hump-shaped relationship between population density and local employment growth in the case of services: the positive effect of overall population density fades as the density of economic activities reaches some threshold value, after which congestion costs overcome agglomeration externalities. In the case of manufacturing, the effect of density is monotonically negative.

The chapter by Massimiliano Agovino and Agnese Rapposelli investigates the influence of agglomeration externalities and spatial spillovers on the production process of Italian regions. To this purpose, they estimate a stochastic frontier production function controlling for spillover effects. Two main findings arise from these estimated results: first of all, the dynamics of regional production are highly interdependent (spatial spillovers are significant and positive); second, their link intensity grows as the distance among regions is reduced. In particular, regions surrounded by neighbors with a high propensity to growth tend to have a greater development, all other things being equal. The opposite effect is obtained for regions surrounded by neighbors with a low propensity to growth. These findings open new directions for future research, particularly in the investigation of the sources of spillovers between geographical regions. Their existence also raises a question about the design and the scope for policies to stimulate development at the local level. In particular, policies with the aim of encouraging local development should consider the externalities that may occur between neighboring areas as a result of their actions, and if they turn out to be positive, the competent authorities should facilitate their dissemination. In this case, due to spillover effects, it would develop a "domino effect" that would involve not only the region where local development policy has been implemented, but it would also positively affect the neighboring regions.

The contribution by Giuseppe Croce, Edoardo Di Porto, Emanuela Ghignoni, and Andrea Ricci deals with the uneven distribution of innovation among geographical areas. Indeed, if the average propensity of firms to undertake innovative activities and investments differs, it may be expected that also firms' performance and labor productivity will differ as well. This work offers a new look on this topic by exploiting the information on the employer's individual profile provided by a firm-level survey recently conducted by the Italian Institute for the Development of Vocational Training for Workers (ISFOL). In particular, they consider if the schooling level of the employer affects the probability that the firm innovates. This makes it possible to shed more light into the "black box" of the innovation process and allows the authors contributing to the existing literature with new empirical evidence relative to the case of Italy. Furthermore, they test if innovation is affected by agglomeration factors as computed by combining provinces and industries. To this end, various density indicators are tested. Beside standard measures of density, following the literature on knowledge spillovers, the authors consider also an original indicator, namely the share of college graduated employers, as a possible factor affecting the innovation propensity in local areas. Both product and process innovations are taken into account. Moreover, according to the peculiarities of the Italian economy, the analysis distinguishes between small and larger firms. To deal with endogeneity issues, an IV approach is applied based on three different instruments. Overall, the results show that the employer's schooling represents a primary factor associated to the innovation propensity of small firms while its effect disappears for larger firms. On the other hand, contrary to the knowledge spillover hypothesis, there is no effect of density. On the contrary, when small firms are considered, density exerts a negative effect suggesting that in the Italian context, innovation by small firms is discouraged in denser areas as they suffer from the fiercer competition for specialized inputs, such as skilled workers.

Part III focuses on new determinants of regional unemployment, namely the location of innovative economic activities, sectors with a higher investment level in R&D, and a greater attractivity to direct investment from abroad.

The first chapter in this part is by Massimo Armenise, Giorgia Giovannetti, and Gianluca Santoni, who focus on business services. The latter are an important component of the competitiveness of a country, not only because of their direct effect on the economy but also for their impact on manufacturing. The development of the business services sector allows manufacturing firms to outsource tasks and activities to "specialists", who can perform them at lower costs and possibly better. In Italy, the business services sector depends crucially on foreign inflows, and the small size of Italian firms suggests that for them to outsource is more feasible than internalizing the services (which would be too costly).

In their paper, the authors analyze the effect of foreign direct investment in business services on Total Factor Productivity (TFP) of Italian manufacturing firms, over the period 2003–2008. More precisely, they test for the presence of vertical linkages between foreign business professionals and domestic manufacturing firms at a highly disaggregated geographical level (i.e., Italian provinces). Their results, which are consistent across provinces, sectors, and several econometric specifications, show that Foreign Direct Investment (FDIs) in business services have a positive impact on TFP. However, their effect differs depending on the level of technology of the sectors and on the availability of skilled labor in the province; high-tech sectors such as mechanics and machinery seem to benefit more. From a structural point of view, the presence of foreign business professionals has a significant aggregate impact on Provinces' economies. The increase in efficiency in production processes, in fact, is likely to generate a greater market for skilled labor and as a result a growth in employment and wages in the long run. Hence, to reduce the barriers, still protecting FDIs in services may turn out to be a positive sum game: foreign service providers can bring in new technologies and know how providing services needed by Italian manufacturing firms to keep (or enhance) their competitiveness and possibly generate a catching-up process among Provinces.

The chapter by Claudio Cozza and Francesco Schettino conducts an empirical study of the patenting propensity at the European regional level using the OECD-REGPAT dataset, in order to depict the existing territorial differences in productivity levels and the structural changes in some sectors. The main novelty of this analysis consists of considering patent applications by inventor's region, a linkage to the territory stronger than using applicant's region. Data analysis reveals the existence of a deep, uneven distribution of patent applications, R&D expenditure, and human capital. Richer regions show higher levels of both private and public R&D expenditure as well as a consistent share of the total European patent applications: these elements could be useful to explain the higher degree of divergence across EU countries and regions. Starting from the analysis of these key variables, the authors proceed by explaining the determinants of the patenting propensity. Applying GMM methods, they obtain results that substantially confirm the significant role of R&D expenditure on patenting activity: mainly the business enterprises but also the government sector component. Human capital variables show a similar positive effect, while average enterprise size seems not to play a determining role in patent applications.

The starting point of the chapter by Carmen Aina, Giorgia Casalone, and Paolo Ghinetti is that education is a key factor, directly or indirectly (through the labor market), of migrants' integration. Italy represents an interesting case to study the integration process of migrants, as it has experienced internal massive flows from less to more developed areas. This chapter analyzes the role of internal geographical mobility on the educational choices of a cohort of young individuals. In particular, the work investigates the imbalances between "natives" and "internal migrants" on the probability of dropping out from the education system at the end of compulsory schooling for a cohort of individuals born between 1979 and 1995 from Italian parents of different geographical origins. Data from the last seven cross sections (1998–2000–2002–2004–2006–2008–2010) of the Bank of Italy Survey of Household Income and Wealth (SHIW) are used. In this sense, it represents the first attempt to analyze the heterogeneous educational outcomes of "natives" vs. "second generation internal migrants" on a sample representative the entire Italian population. The main finding is that in terms of educational achievements, children born in Northern regions with parents (both) migrated from Southern Italy perform very similarly to their peers who live in Southern Italy, i.e., they experience a greater probability to drop out from school early, ceteris paribus. The incomplete integration process of internal migrants raises doubts on the possibility to integrate migrants from abroad throughout the educational system in Italy.

In their chapter, Claudia Pigini and Stefano Staffolani study the enrollment decisions of Italian secondary school graduates. They relate this decision to the cost of participating in higher education explicitly considering tuition fees and the cost of moving to other locations. By looking into the role of incentives, such as scholarship grants and the supply of under-priced accommodation, which are policy tools in the hands of regional institutes, the authors provide empirical evidence of the consequences of changes in public policy on enrollment rates and students mobility.

Using the ISTAT survey of secondary school graduates in 2004 interviewed in 2007 linked with data on institution's characteristics from the Italian Ministry of Education, University and Research (MIUR), the authors present descriptive statistics on the "attractiveness" of Italian regions in terms of higher education opportunities and estimate four different conditional logit model specifications where each secondary school graduate chooses between enrolling in one of the Italian universities and non-enrolling. In this setting, the choice probability is allowed to depend on tuition fees, grants, house rent, distance between the student's home and the university, and on many territorial covariates such as quality of life, population, and unemployment rate of the provinces where universities are located.

Their empirical strategy provides straightforward post-estimation analyses on the main instruments in the hands of the university and regional management for policy tuning, that are tuition fees, expected grants, and expected rent; on average, the elasticity of the probability of enrollment to tuition fees is −0.062, the one to expected grants is +0.028, and the one to expected rent is −0.022. There exist market differences between regions: southern regions show lower elasticities, whereas small central and northern regions the largest ones. Regional differences emerge also because of the accessibility to more opportunities to substitute the choice of which university to enroll into. The findings also confirm that the geographical distance plays a major role in students' choice between universities: students prefer to enroll in universities close to home, implying that they may settle for choices that do not fit at best their ability and preferences. In addition, a key role in university choice is played by the socioeconomic conditions of the institution geographical location, suggesting that the process of choosing a university may hide the search for better job opportunities.

The contribution by Justina AV Fischer on globalization and female employment in OECD countries focuses on regional and territorial imbalances w.r.t. trade effects for national labor markets and analyzes how trade supports the convergence of employment patterns between men and women in OECD countries. The chapter highlights: (a) that information globalization has distinct effects compared to international trade; and (b) that local (regional) and nation-wide effects of these dimensions of globalization exert differential impacts. The preceding literature has neglected both issues—that of globalized information that evolves in parallel with the exposure of an economy to world markets, and that of regional-spatial aspects. In addition, most previous studies look at aggregate effects only, while Fischer's contribution employs information on 110,000 persons derived from the World Values Survey, who had been interviewed between 1981 and 2008. She conjectures that informational globalization affects societal values and perceived economic opportunities, while economic globalization impacts actual economic opportunities. Her study reveals that both appear to increase the employment probability of women compared to men's. When accounting for sub-national regional gender heterogeneity, the impact of worldwide information exchange works rather at the regional level, while economic globalization (int'l) appears to increase female employment in general.

Part IV focuses on three policy interventions: the EU structural funds, the program for self-employment, and macroeconomic policy. The first two chapters in this part provide a range of methodological tools for policy evaluation, which are important for the development of an evidence-based regional policy. The third chapter contains a suggestion which is useful for policy maker, namely to measure local GDP by using regional PPP deflators in order to catch the impact on wage differentials of local price dynamics. It is now time to develop a new approach to policy making, also regional policy making. To paraphrase a statement by Zimmermann (2014), it is important that also regional policy be evaluated not to understand whether it is right-wing or left-wing, neoclassical or Keynesian, but whether it was correct or wrong, effective or ineffective. The available studies show that regional policy tends to have little effect. It is only through rigorous evaluation studies that it will be possible to identify factors that might favor the success or failure of regional policy.

In their chapter, Gianluigi Coppola and Sergio Destefanis assess the effect of the European Structural Funds on the economies of the 20 Italian administrative regions for the period 1989–2006. The importance of this work is due to the fact that the empirical results presented in the previous literature are discordant. The application of econometric models yields different and occasionally opposite results, mainly depending on the dataset used, the period considered, and the method applied. They can be classified into three groups. The first group of papers, among others Boldrin and Canova (2001), finds a negative, or nearly insignificant, impact of the Funds on the convergence process. On the contrary, the second group finds that the impact is positive (i.e., Garcìa-Solanes and Maria-Dolores 2002a, b), while the third group argues that the effects of the Funds crucially depend on the initial conditions of the regions where they are allocated (i.e., Aiello and Pupo 2007).

The principal novelties of Coppola and Destefanis's paper are that the empirical analysis separately considers the effects of the Funds on four sectors (agriculture, energy and manufacturing, construction, and services), and that a decomposition of productivity changes, based on a Malmquist productivity index, is produced. They find that the Funds had a weak, but significant, impact on total factor productivity but virtually no effect on capital accumulation or employment. Moreover, different types of Structural Funds are found to have widely different influences, with the European Social Fund, arguably, having the strongest impact.

Matías Mayor, Begoña Cueto, and Patricia Suárez address one of the policy tools often suggested, also by EU and other international institutions, as a means to reduce, especially, youth unemployment, which is typically pooling in high-unemployment regions not only in the Mediterranean countries.

The capitalization of unemployment benefits stands out as the main program to foster self-employment among unemployed people in Spain. In this chapter, the authors evaluate for the first time its impact on regional unemployment, contributing to the scarce evaluation of active labor market policies in the Spanish context. Data from the Spanish Provinces during the period 2003–2009 are used.

The most important stylized fact of the Spanish labor market is the existence of major differences in regional unemployment rates and their temporal persistence. Additionally, entrepreneurial activity tends to be clustered geographically in Spain. Consequently, these geographical differences may require the inclusion of spatial issues in the explanatory model. The second contribution is the methodological approach, which explicitly incorporates the spatial autocorrelation processes in both the unemployment rate and in the capitalization of unemployment benefits, by using a spatial Durbin model. The authors obtain low values for both direct and indirect effects, thus supporting the idea that this kind of programs has high deadweight effects, which means that the contribution to the reduction of unemployment is low.

The issues concerning the evolution of regional labor market disparities within Central and Eastern European countries have been thoroughly discussed in many papers. Still, most of them have focused on the persisting differences in the regional unemployment rates. At the same time, the dispersion of wages across different locations and its evolution over time have been considered as one of the possible factors influencing spatial unemployment rate differentials.

The chapter by Bartlomiej Rokicki adds to the existing literature by showing the results of calculations concerning regional PPP deflators in Poland at the NUTS2 level and their impact on the analysis of regional wage differentials. In particular, it verifies the real wage equalization hypothesis in the case of Poland between 2000 and 2011 and shows what happens to the level of regional income disparities and their evolution over time once we apply regional PPP deflators instead of average deflators for the country as a whole. He finds that the application of regional PPP deflators significantly decreases the overall level of wage disparities across Polish regions (as compared to nominal wages). Nevertheless, it does not significantly change the overall pattern of their evolution.

Up to now, all papers focusing on the evolution of regional wage differentials have not taken into account possible differences in the level of prices between different regions within the same country. As a result, they neither show the existing regional differentials in real wages nor their evolution. Hence, they can only partially explain the reasons behind the persisting regional labor market performance differences. Here, these are the real wages that attract labor force to certain areas increasing their productivity and thus reinforcing existing regional unemployment disparities.

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Biography

Chiara Mussida received her B.A. and Ph.D. in Economics from Università Cattolica del Sacro Cuore (Piacenza and Milan) in 2005 and 2009, respectively. Between 2006 and 2007, she also studied at the University of Sussex (Brighton, UK), where she obtained a Master of Arts in Development Economics (2007). She also collaborated with national and international research centres. She is an Assistant Professor at the Department of Economic and Social Sciences, Università Cattolica del Sacro Cuore (Piacenza), since December 2012. Her research interests include labour economics and microeconometrics.

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Part I
Determinants of Regional Unemployment

Chapter 2
Worker Turnover Across Italian Regions

Chiara Mussida and Francesco Pastore

Abstract This chapter provides prima facie evidence of the geographical distribution of worker turnover within Italian regions as measured based on the longitudinal files of the labour force survey (LFS) for the period 2004–2010. It explains the stylized facts emerging from this enquiry with an interpretation based on the industrial change literature. Industrial turbulence, rather than labour market flexibility, is driving labour turnover within regions, as the correlation with the Lilien (positive) and the Herfindahl (negative) indices, respectively, shows. In other words, industrial change causes greater job destruction and flows into and out of unemployment, while, as also Alfred Marshall noted, the availability of more specialised districts could partly offset the diseconomies of specialisation in terms of greater exposure to external shocks, when the unit of analysis is sufficiently large, as it is in our case (NUTS1 and NUTS2). We also find that, at an individual level, the regional gap in turnover rates is due to regional differences in the gender, age and education attainment of the workforce, as well as the share of temporary work contracts and the size of firms.

Keywords Regional unemployment • Industrial change • Worker turnover • Italian regions

JEL Classification C33, J63, P25, P52, R23

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2.1 Introduction

The literature offers different interpretations of the relationship between worker turnover and unemployment rate, especially at the regional level. A relevant explanation hinges on the so-called Lilien hypothesis, according to which industrial restructuring causing sectoral shifts might explain the high level of turnover of high-unemployment regions. Alternatively, large labour market flows might be the sign of greater labour market flexibility, which is, however, usually associated with efficient labour markets and, thus, relatively lower unemployment, the so-called Krugman hypothesis.

In this chapter, we empirically discriminate between these alternative theoretical hypotheses by exploiting the geographical differentiation of worker turnover and unemployment rates in the case of Italy, by investigating the determinants of labour turnover at a regional level by using the longitudinal files of the LFS data over the period 2004–2010. To our knowledge, this is the first paper to study in a systematic way the geographical relationship between the rate of worker turnover and the rate of unemployment in Italy using LFS data. Until recently, indeed, statistical information on worker turnover based on individual-level survey data was not available. Ferragina and Pastore (2008) suggest that this test constitutes a 'screening device' to distinguish the case when unemployment is due also to some region-specific shock, namely the high degree of worker turnover in high-unemployment regions is caused by industrial restructuring and when it is instead due solely to labour market rigidities.

Note that the policy implications of these alternative hypotheses are partly different, since a low job finding rate in high-unemployment regions essentially suggests the need for supply side policies, whilst a positive relationship between labour market turnover and unemployment requires interventions on the demand side as well.

The empirical evidence available in the literature on this issue is neither large nor unambiguous. The main reason is the limited availability of suitable longitudinal data to measure labour market dynamics at the local level. A number of papers find a positive relationship between worker turnover and the regional unemployment rate (for the UK: Armstrong and Taylor 1985; for Poland: Newell and Pastore 2006; Pastore and Tyrowicz 2012; for Italy: Contini and Trivellato 2005; Naticchioni et al. 2006; Basile et al. 2012), others find no relationship (for a bench of Eastern European countries: Boeri and Scarpetta 1996; WorldBank 2001; Rutkowski 2003; for the UK: Robson 2001).

In addition, the sign of the relationship under scrutiny might change over time, which has never been accounted for earlier. Except for Pastore and Tyrowicz (2012) and Basile et al. (2012), whose data include a panel dimension, previous research was mainly based on analyses of short periods of time, often 1 or 2 years. Although not being panel, the LFS longitudinal data used here covers quite a long period of time.

The purpose of our analysis is twofold. First, we aim at understanding the nature of the relationship between local worker turnovers.[1] Second, based on the nature of the relationship under scrutiny, we aim at understanding the sources of worker turnover and how it differs across regions. We use the micro-dimension of the data to study the determinants of worker turnover at the individual level. This allows us controlling for factors that might be important correlates of worker turnover and unemployment rates at a local level.

The case of Italy is particularly interesting not only because of its well-known and persistent regional unemployment differences but also because it allows comparing the better developed more dynamical regions of the North and the static regions of the South.

One explanation of the geographical differentiation of worker reallocation (WR) and worker turnover (WT) hinges on the differences in the local labour market structure (e.g. OECD 2004). We study the correlation of WT across geographical units not only with the level of industrial turbulence but also with that of unemployment.

We find evidence of a positive relationship between WT, on the one hand, and the unemployment rate across regions, on the other hand. Quite surprisingly, for those who consider WT as a proxy for labour market flexibility, in all the considered years, indeed, the rate of turnover is higher in those regions where also the unemployment rate is higher. The high-unemployment South is the geographical area with the highest WT especially with respect to the North-West.

To examine the possible sources of regional differences in worker turnover, we carry out econometric estimates of the determinants of the WT rate in pooled estimates for the period 2004–2010. In a first attempt, we added control variables for such individual characteristics as age, gender and education, type of occupation, sector of activity (public versus private), firm size and type of labour contract (permanent versus temporary). All the considered explanatory variables play a statistically significant role. Similar to what previously found in Newell and Pastore (1999) with reference to Poland, the youngest age segment shows a highest probability of turnover as compared to the other age groups, with the partial exception of the eldest workers. This latter, indeed, more frequently move to inactivity.

WT reduces with education and age, as expected also based on previous studies (e.g. Naticchioni et al. 2006), with firm size and in the case of workers employed in the public sector. On the other hand, WT increases for temporary workers. In our estimates, we also include indicators of sectoral shifts and industrial concentration as possible sources of worker turnover and of its regional differences. We find that those indicators are quite relevant determinants of worker turnover and of its geographical discrepancies. As to the effect of structural change and economic diversification, we find that WT is positively related to structural change, as measured by the Lilien index, and negatively related to the degree of industrial concentration, as measured by the Herfindahl index. Once we control for these two

[1]The definition of worker turnover, derived from Davis and Haltiwanger (1995), will be given in Sect. 4.1.

factors, we note a reduction of between 21 and 43 % of the unconditional gap across regions in terms of WT.

The chapter proceeds as follows. Section 2.2 offers a survey of the relevant theoretical foundations as well as some available empirical evidence. Section 2.3 implements the descriptive and the econometric analyses. Section 2.4 discusses our findings. Section 2.5 concludes.

2.2 The Theoretical Hypothesis on the Relationship Between Worker Turnover and Unemployment

The Aghion and Blanchard (1994) model and its development by Boeri (2000) can be used as a theoretical framework to think of the way how labour market dynamics, as measured by WT, affects the regional distribution of unemployment.[2] As Ferragina and Pastore (2008) argue, although used to explain national unemployment, this framework might also apply to local labour market differences, provided that regions are separated from each other due to low internal migration, as it is the case of many European countries, including Italy.

The theoretical framework offers three alternative hypotheses on the nature of the relationship between WT and regional unemployment. First, WT could be independent of regional unemployment. According to this hypothesis, the same aggregate shock yields asymmetric effects across regions. High-unemployment regions are such because they have experienced dramatic structural change sometime in the past, with a too high separation rate at the beginning, so that the unemployment rate exceeds its equilibrium level. Only at a later stage, separation rates converge across regions.

Second, worker turnover could positively correlate with regional unemployment. This might happen because in high-unemployment regions, more jobs are destroyed and created at the same time, i.e. each region has a specific rate of structural change, but other hypotheses are also possible, as later discussion will show.

The well-known Krugman (1994) hypothesis could provide an explanation for the third hypothesis, i.e. WT correlates negatively with regional unemployment; greater WT would mean, in fact, a higher degree of labour market flexibility and, therefore, lower frictional and long-term unemployment. In other words, there would be a spatially asymmetric impact of rigid labour market institutions.

The literature shows that the sign of the relationship under consideration might change according to the country considered, the data used and over time. Robson (2001), for instance, finds no correlation between worker reallocation and unemployment across the UK macro-regions in the decade 1984–1994. In the case of new EU members in Eastern Europe, some authors (such as Boeri and Scarpetta 1996; World Bank 2001; Rutkowski 2003) interpret the low rate of monthly worker

[2] For details on the theoretical framework, see Pastore (2012).

turnover computed as based on employment registry data of high-unemployment regions as a consequence of low labour market dynamism.

Garonna and Sica (2000) find a negative association between the Lilien index of structural change and the unemployment rate in Italy: in particular, sectoral and interregional reallocation in Italy would reduce unemployment.

Other studies find evidence that high-unemployment regions are those where the degree of worker turnover is higher. For Poland, Newell and Pastore (2006) use LFS measures of annual gross worker flows and find a correlation coefficient between the job separation rate and the unemployment rate of 0.76, significant at the 1 % level, during the period 1994–1997. Pastore and Tyrowicz (2012) confirm previous findings regarding Poland using employment registry level data relative to the period 2000–2008.

For Italy, Contini and Trivellato (2005) find the highest turnover rate in the traditionally high-unemployment regions of Mezzogiorno. Naticchioni et al. (2006) find similar evidence using the ISFOL data relative to the period 1994–1998. Using Local Labour Systems (LLSs) panel data relative to the years 2004–2008, Basile et al. (2012) also report a strong correlation between worker reallocation and unemployment across LLSs. Sectoral shifts and the degree of specialisation exert a negative role on unemployment dynamics.

Revisiting this issue, Shimer (2007) has recently proposed a new methodology which points to the fact that the evolution of the job finding rate—and not that of the flow into unemployment—would reproduce the cyclicality observed in the unemployment rate. Fujita and Ramey (2009) find that cyclical changes in the separation rate are negatively correlated with changes in productivity and move contemporaneously with them, whereas the job finding rate is positively correlated with and tends to lag after productivity, which is consistent with the Aghion and Blanchard (1994) theoretical framework adopted in this chapter.

The literature also offers some explanations on the sources of WT and its differences across regions. In particular, if WT correlates positively with regional unemployment, as it is the case for Italy, the following explanations are offered. The Lilien hypothesis states that differences in the sources of WT are primarily due to different sectoral shifts across regions.

According to this hypothesis, some sectors/regions experience a permanent reduction in labour demand that causes local unemployment. Lilien (1982) found a positive correlation over time between the aggregate unemployment rate and the cross-industry dispersion of employment growth rates in the USA.

For measuring structural change in the demand for employment, Lilien developed an index that measures the standard deviation of the sectoral growth rate of employment from period $t-1$ to period t. For each region (or geographical area) of the country, the Lilien index is used to measure the rate of industrial or structural change in the demand for labour by means of the variance in industry employment growth.

Most studies in this literature use some variation of the Lilien index: Berg (1994) for Canada, Newell and Pastore (2006) for Poland, Krajnyàk and Sommer (2004) for the Czech Republic and Robson (2009) for the UK.

It is perhaps important to mention that there are sources of industrial turbulence that tend to be transitory and others that are permanent. The former include the opening up to international trade of new competitors and the introduction of new technologies causing some productions to go out of market. Structural and permanent 'weaknesses' of high-unemployment regions, which cause their low competitiveness and attractiveness to investment from abroad, include: (a) low human (Carillo and Zazzaro 2001) and social capital (Bagnasco et al. 2001; Lopolito and Sisto 2007; and references therein) endowment; (b) low effectiveness of public administration and a high rate of corruption (Del Monte and Papagni 2001); (c) high (organised) crime rates (Centorrino et al. 1999; Centorrino and Ofria 2001; Daniele and Marani 2011); (d) industrial dependence on more developed regions; (e) poverty traps (Carillo et al. 2008). All these factors may reduce the competitiveness of firms and cause higher than average mortality rate for firms and, consequently, also a higher degree of job destruction.

To overcome the criticisms against the Lilien index and its variations, research in the field has pursued the aim of finding empirical ways to disentangle sectoral shifts and aggregate disturbances. Among others, Neumann and Topel (1973) elaborate a macroeconomic model where the equilibrium level of unemployment in a region depends on its exposure to the risk of within-industry employment shocks and on their degree of industrial diversity. Their approach has stimulated further research.

Following Neumann and Topel (1973), several authors (e.g. Simon 1988; Simon and Nardinelli 1992; Chiarini and Piselli 2000; Basile et al. 2012) have tried to control for aggregate disturbances including in the estimates some index of industrial concentration, such as the Herfindahl–Hirschman index (HHI).[3]

The rationale is that common shocks may generate asymmetric effects across industries. In fact, regions that are highly specialised in low-sensitive industries are expected to exhibit low vulnerability to aggregate disturbances, and vice versa. The HHI index is often used in the literature as a control variable to measure the impact of aggregate disturbances. It is taken to measure the vulnerability of specific areas (e.g. regions) to aggregate shocks in regressions of the determinants of WT. In detail, if the sign of the HHI is positive, a higher rate of industrial concentration is a positive correlate of the degree of WT and, therefore, of unemployment. Conversely, if the HHI is negative, the correlation between industrial specialisation and unemployment is negative. Different competing hypotheses have been set in the literature to explain the relation between WT and HHI or industrial concentration.

More generally, two alternative hypotheses are in order as to the local impact of aggregate shocks: According to Jacobs (1969), aggregate shocks should hit more the least diversified regions because of what Simon and Nardinelli (1992) called the portfolio effect in the labour market; vice versa, Glaeser et al. (1992) pointed

[3]For details on the HHI index, see Mussida and Pastore (2012).

to Marshallian effects to suggest that more specialised industries might provide higher positive externalities and growth which should absorb the negative effect of aggregate shocks. Marshall (1890) himself noted also that the negative employment effects of aggregate shocks on specialised areas may be reduced in large regions, in which several distinct industries are strongly developed (for surveys of this literature, see, among others, Elhorst 2003; Ferragina and Pastore 2008). In the case of Italy, Basile et al. (2012) find evidence of the portfolio effect using data at a local labour market system level (travel to work areas).

Alternatively, Burgess (1993) assumes that the greater worker reallocation rate in high-unemployment regions is due to the relatively smaller number of job opportunities for unemployed job seekers in low-unemployment regions. In other words, in the latter regions, the unemployed are crowded out by employed job seekers who are encouraged to search for better jobs. Consequently, one would observe a higher rate of worker turnover in high-unemployment regions simply because in these regions, the unemployed who find jobs are a relatively larger number with respect to their peers in low-unemployment regions.

2.3 Methodology and Data

Our sample is extracted from the ISTAT LFS data. This is a rotating panel survey based on the principles set out by the International Labour Organisation (ILO) and on harmonised methodology across most of the countries in the OECD area. The longitudinal component of the survey comprises almost 70,000 individuals per year.[4]

We focus on annual flows over the years 2004–2010 of all the employees aged 15 through 64. We drop individuals over the age of 64 to avoid getting mixed up with retirement issues. We also drop the self-employed, the individuals who were in the army or with missing values for some important variables used in the econometric analysis. We remain with 129,597 observations.

The purpose of our descriptive analysis is to test the alternative hypotheses presented in Sect. 4.1 regarding the nature of the link between local worker turnover and unemployment by looking at unconditional means across regions. Note that in the theoretical literature, worker reallocation is meant in a more general way as a reallocation of workers from a declining to an expanding sector, with or without intervening unemployment spells. The definitions adopted in this chapter are essentially based on Davis and Haltiwanger (1995), and the relevance of such indicators is examined by, among others, Davis et al. (1996), and, for Italy, by Contini (2002) and Naticchioni et al. (2006). Both worker turnover and worker reallocation are measured at the worker level (individual-level data), whilst job turnover and job reallocation are measured at the firm level (firm-level data).

[4]For details, see Discenza and Lucarelli (2009), and ISTAT (2006, 2009).

Being based on individual-level data, our essay studies worker flows. Worker turnover (*WT*) at time *t* is the number of accessions to employment from unemployment and inactivity plus the number of separations from employment to unemployment and inactivity, respectively. Therefore, *WT* does not include flows between unemployment and inactivity. The *WT* rate is computed by dividing WT by the average employment level (between $t-1$ and t). In our analysis, we calculate *WT* at the geographical level of *NUTS*1 and *NUTS*2, i.e. macro-regions and regions.

The aim of the econometric analysis is to study the relationship between the regional unemployment rate and the rates of WT controlling for a number of variables that could in principle affect the geographical distribution of WT. In other words, after assessing the sign of the above relationship in terms of unconditional means, which we do in the descriptive analysis, we then test its robustness by means of multivariate analysis in a micro-econometric context.

The factors behind the significant geographical imbalances in WT might be many and independent of differences in the degree of structural change. We carry out logit estimates taking as a dependent variable, the fact of having experienced a worker turnover flow in the last year, as defined in the previous section. We pool all the observations over the years 2004–2010. We consider a number of control variables that might explain worker turnover across regions, such as individual characteristics (i.e. gender, age and educational level), the region of residence (three macro-areas of residence, i.e. North-West, North-East and Centre-South), and additional variables that proxy firm size, sector of employment (public/private) and type of labour contract (fixed term or permanent). In order to take into account possible time trends, we also control for the year over which flows are computed by means of yearly dummy variables.

The regional dummies are our variables of interest. We aim to test whether regional differences in WT continue to be there also after introducing a number of control variables which might also explain regional differences in WT. Take, for instance, firm's size which is an indicator of market structure. Differences in the market structure, indeed, might explain differences in worker turnover at the local labour market level; the more competitive is the market structure in the local economy and, therefore, the greater is the share of small-sized firms, the greater is also the degree of worker turnover. More in detail, the available literature, such as OECD (1994), and for Italy Boeri (1996) and Naticchioni et al. (2006), shows that gross flow rates are inversely related to firm size.

The latter contribution finds that in Southern Italy, the share of employment in small and medium-sized firms is higher than in the rest of the country, especially if compared to the North-West. The economic structure of these areas might affect the overall turnover rate. In other words, the higher the share of employment in small firms, the higher will be the flow rates.

Differences in the age of individuals living in different regions might also affect the WT gap. The higher is the proportion of young people living in a region, the greater, ceteris paribus, its degree of turnover is expected to be. A greater concentration of low-education and low-skill workers and a higher share of temporary and informal workers tend also to be associated with a higher probability of WT.

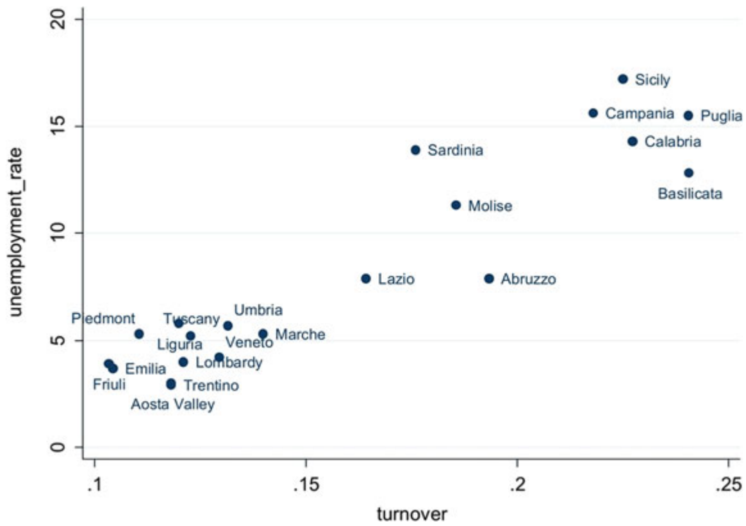

Fig. 2.1 Regional unemployment and worker turnover, 2004–2005

2.4 Findings

2.4.1 Descriptive Analysis

Figures 2.1, 2.2, 2.3, 2.4, 2.5 and 2.6 provide evidence supporting the first hypothesis of Sect. 4.1, i.e. WT correlates positively with regional unemployment, in all the considered years. Figure 2.7 also confirms these findings. The rate of worker turnover is higher in the regions where also the unemployment rate is higher.

In addition, we show that there is also a positive relationship between the regional rate of unemployment and the two components of worker turnover, namely the inflow to (Fig. 2.8) and outflow from (Fig. 2.9) unemployment, as expected considering the long-run equilibrium relationship existing among these two variables.

We indeed find the highest turnover rates in the traditionally high-unemployment regions of the South of Italy (about 22–24 %), namely in Campania, Puglia and Sicily, which exhibit also the highest unemployment rates (about 15–17 %). This pattern is confirmed for the entire period examined. In detail, Campania maintains the highest worker turnover rate for the period 2004–2010, whilst Sicily maintains the highest unemployment rate. The regions of the North of Italy, instead, maintain lower turnover and unemployment rates.

This finding is in line with what Contini and Trivellato (2005) found on LFS data for the decade 1993–2003 and Naticchioni et al. (2006) found on ISFOL data for

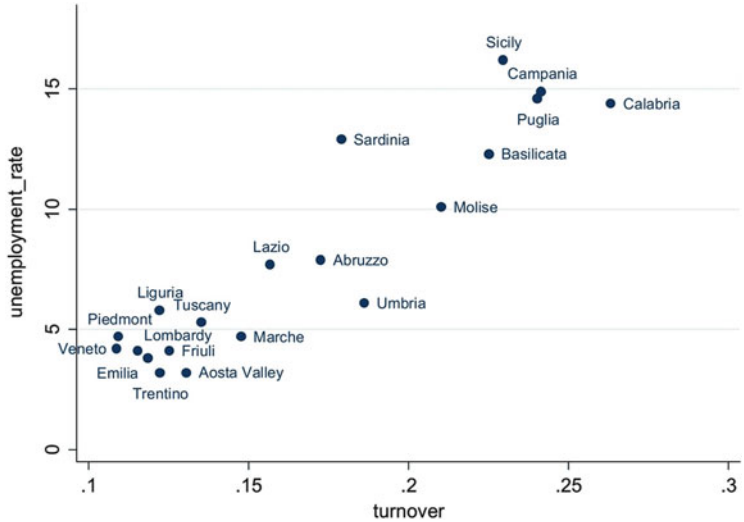

Fig. 2.2 Regional unemployment and worker turnover, 2005–2006

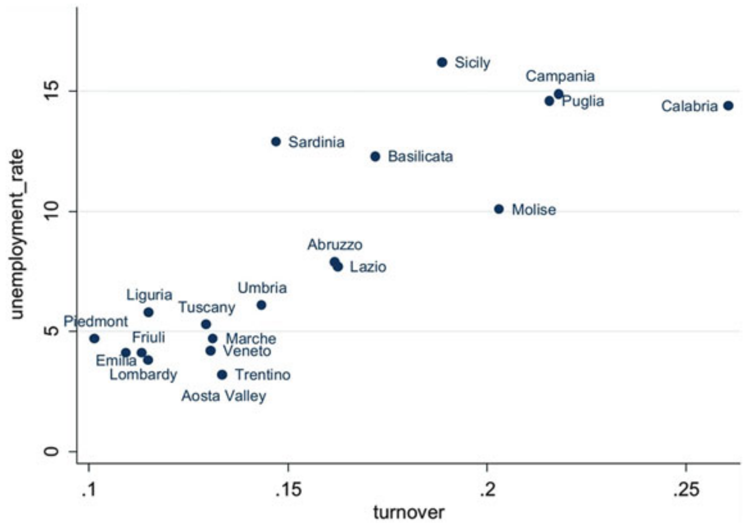

Fig. 2.3 Regional unemployment and worker turnover, 2006–2007

the period 1985–1999. Both these previous research works find a positive relation between worker turnover and regional unemployment.

We also compute the worker turnover, together with its main components of the inflow and outflow rates, at the NUTS1 level (macro-regions). We find that the South is the area with the highest worker turnover rate and of both its components.

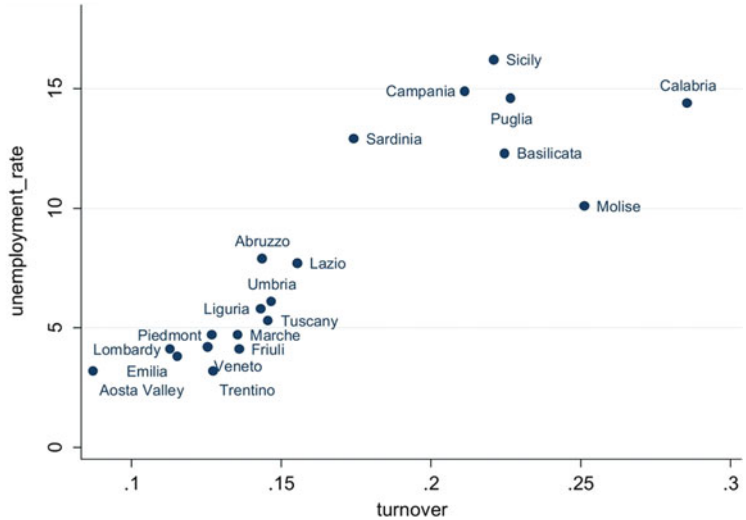

Fig. 2.4 Regional unemployment and worker turnover, 2007–2008

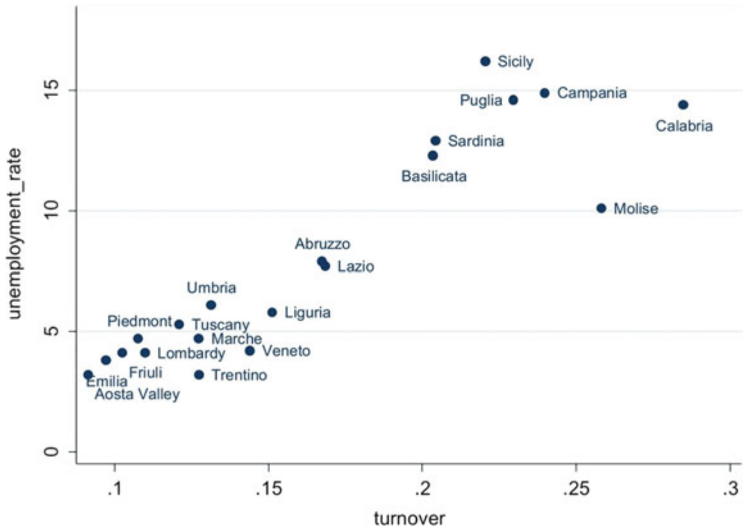

Fig. 2.5 Regional unemployment and worker turnover, 2008–2009

In 2005–2006, the accession and separation rates of the North are half those of the South. In other words, the degree of turnover is higher in the South than in the North, which may mirror the role of temporary work and the precarious nature of work experiences in this area of the country.

WT exceeds 14 % throughout the entire period and is quite stable during the years and independent of the recession, which reached the labour market only at the end

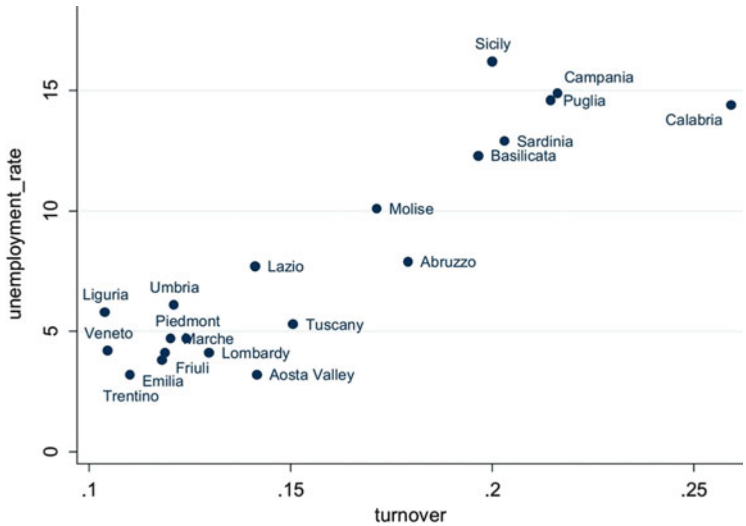

Fig. 2.6 Regional unemployment and worker turnover, 2009–2010

of 2011. As expected, the recession has reduced the accession rates and increased the separation rate from employment. Those two effects cumulate with each other, increasing the unemployment rate, but still only to a small extent, if compared with what has happened in the years after 2011.

2.4.2 *Econometric Analysis*

To understand the possible sources of WT and the reasons behind the geographical differences, we estimate a simple logistic model of the probability of an individual to experience a change in his or her labour market status in a given year, using pooled data relative to the overall period for which the data is available (2004–2010). Our general hypothesis, discussed at length in Sect. 4.2, is that, ceteris paribus, a greater degree of *WT* is related to a higher incidence of industrial turbulence in the high-unemployment regions, as based on the Lilien hypothesis.

We estimate five different models. Model (1) includes the areas of residence only. Model (2) introduces individual-level control variables, which might also affect WT. The Models (3) and (4) introduce also the Herfindahl and the Lilien index, respectively, our variables of interest.[5] Finally, Model (5) includes all the

[5]The Lilien index is computed by using the STATA command Lilien as explained in Ansari et al. (2014).

Fig. 2.7 Turnover rate by region

explanatory variables together.[6] Following the hypothesis explained above, in fact, it is reasonable to expect that a significant part of WT be explained by industrial change, controlling also for the so-called portfolio effect. In the first exercise, the regional dummies, taking the Centre-South as base category, appear to be significantly different from one another for the overall period. The Centre-South is confirmed to be the area with the highest rate of WT, especially if compared with the North-West of the Country. The gap between Centre-South and North-West is of about 44.1 %. The percentage is a bit lower (around 42.7 %) for the North-East.

In model (2), we add all the other possible sources of WT at an individual level. As noted above, the Centre-South has, to a greater extent than the other regions, most of the characteristics that are generally associated with higher WT. We, therefore, expect that adding control variables should reduce the regional gap in WT observed in unconditional estimates. We find that all the control variables play the expected role on WT, but the ranking of the coefficients of regional dummies

[6]For shortness sake we omit the estimates, which are, however, available upon request.

Fig. 2.8 Inflow Rate by Region

remain partially the same. The Centre-South is again the area with the highest rate of worker turnover. Interestingly, the gap between Centre-South, on the one hand, and North-West and North-East, on the other hand, becomes now very similar. The role of our control variables overall is a slight reduction of about 4 % points (1.5 % points) of the gap in WT between Centre-South and North-West (North-East) of Italy.

Women and the youngest age segment show a higher probability of worker turnover than men and the other age groups. The youngest individuals and women suffer typically of more career interruptions than prime-age workers. The eldest, instead, are more involved in the transitions to preretirement and retirement.

The probability of WT reduces with increasing education and, as expected based on other studies (e.g. Naticchioni et al. 2006), with reducing firm sizes. Lastly and expectedly, worker turnover increases for temporary workers.

To sum up the discussion until now, we find evidence supporting the first hypothesis in all the considered years. We indeed find the highest turnover rates in the traditionally high-unemployment regions of the South of Italy both in

Fig. 2.9 Outflow Rate by Region

unconditional estimates and conditional on several control variables catching the specific characteristics of the geographical units considered.

In model (3) and (4), where we introduce the Herfindahl and the Lilien index, respectively, we find a further reduction in the geographical differential in WT rates. In fact, WT correlates positively with structural change, as measured by the Lilien index, and negatively with the degree of industrial concentration, as measured by the Herfindahl index. Once we control for sectoral shifts and industrial concentration, we note a reduction of between 21 and 43 % of the regional gap in terms of workers' turnover.

The lower than one odds ratio of the Herfindahl index suggests that a higher rate of industrial concentration is a negative correlate of the degree of WT and, therefore, of unemployment; in other words, Marshallian effects would outweigh the portfolio effect. We find higher values of the index and, therefore, a higher degree of industrial concentration in higher employment opportunities regions of the North of Italy than the Centre-South.

Hyclak (1996) also found a negative correlation of the Herfindahl index with the local unemployment rate. Basile et al. (2012) find instead a positive association between the degree of industrial specialisation and local unemployment, suggesting that the local concentration of firms within the same industry might give rise to a lesser number of employment opportunities to dismissed workers, in addition to being more exposed to sectoral shifts.

How to explain the difference between our finding and that of Basile et al. (2012)? The most likely candidate to an explanation is the fact that we look not at local labour systems but at larger geographical units. In the latter case, as also Marshall noted, the availability of more specialised districts could partly offset the diseconomies of specialisation in terms of greater exposure to external shocks. The higher presence of districts in the North of Italy leads to higher employment and industry concentration as measured by the Herfindahl index. Higher employment concentrations reduce the vulnerability (of industries and consequently of workers) into the North of Italy and therefore, the worker turnover (we indeed find lower rates of turnover in the North compared to the South of Italy) and to a wider extent the reallocation of workers.

2.5 Conclusions

The empirical analysis of this chapter builds on the theoretical model laid down in Aghion and Blanchard (1994) [and more recently in Boeri (2000)] and the applications at a regional level suggested by, among others, Ferragina and Pastore (2008) and Pastore (2012).

The previous literature brings to the fore different hypotheses as to the link between local labour market dynamics—as proxied by the worker turnover rate—and the unemployment rate. There are different theoretical explanations of the link between the local rate of worker turnover and of unemployment. The available empirical studies provide different results according to the period, country and type of data used.

In this chapter, an attempt was made to quantitatively verify the empirical pattern linking worker turnover and the unemployment rate using a rich individual-level dataset, namely the longitudinal files of the Italian LFS encompassing the period 2004–2010.

Pooled estimates of the probability of experiencing a worker turnover suggest a statistically significant and economically large difference across regions at both a NUTS1 and NUTS2 level. In addition, such a geographical gap positively correlates with that in unemployment rates. The rate of worker turnover is highest in the high-unemployment area in Centre-South of Italy.

When we look at the determinants of the regional gap in turnover rates, we find that women, the youngest age segment as well as the least-educated employees experience the highest probability of worker turnover. This latter is also associated with temporary work contracts and small firm size. Due to the greater concentration of young workers in small- and medium-sized enterprises, often holding a temporary contract, in high-unemployment regions, we find that the gap between the Centre-

South and the North-West reduces by 18 % and that with the North-East reduces by 11 %.

More importantly, from the point of view of our theoretical hypotheses, we find that worker turnover across NUTS1 and NUTS2 units correlates positively with structural change, as measured by the Lilien index, and negatively with the degree of industrial concentration, as measured by the Herfindahl index. In summary, this chapter has found that the regional gap in turnover rates is due to the differences between regions in the gender of the workforce, the age and education of the workforce, the share of temporary work contracts, the size of firms, the Herfindahl index of industrial concentration and the Lilien index of structural change.

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Biography

Chiara Mussida received her B.A. and Ph.D. in Economics from Università Cattolica del Sacro Cuore (Piacenza and Milan) in 2005 and 2009, respectively. Between 2006 and 2007, she also studied at the University of Sussex (Brighton, UK), where she obtained a Master of Arts in Development Economics (2007). She also collaborated with national and international research centres. She is an Assistant Professor at the Department of Economic and Social Sciences, Università Cattolica del Sacro Cuore (Piacenza), since December 2012. Her research interests include labour economics and microeconometrics.

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Chapter 3
Spatial Patterns of German Labor Market: Panel Data Analysis of Regional Unemployment

Elena Semerikova

Abstract This chapter is devoted to the investigation of spatial spillover effects of the regional unemployment in Germany. Due to historical reasons, the differences between eastern and western regions of Germany persist over time. We explore the differences in the determinants of the regional unemployment as well as the differences in spatial effects by estimating spatial models. We use panel data for 407 out of 413 German regions (using the NUTS III regional structure) for 2001 through 2009. In order to account for possible spatial interactions between regions, we use a spatial weighting matrix of inverse distances. We estimate static and dynamic models by the maximum likelihood estimation approach, developed by Anselin (*Spatial econometrics: Methods and models*, Berlin: Springer, 1988) specifically for spatial models and elaborated by Lee and Yu (*Journal of Econometrics, 154*, 165–185, 2010a; *Regional Science and Urban Economics, 40*, 255–271, 2010b). We reveal that the unemployment in western regions is more of disequilibrium nature, while the unemployment in eastern regions is more of equilibrium nature. Using System GMM approach, we estimate the extended specification of the dynamic model and find that the unemployment in eastern regions affects both the unemployment in western and eastern regions of Germany, whereas the unemployment in western regions has an impact only on other western regions.

Keywords Germany • Regional unemployment • Spatial panel data analysis

JEL classification C21, C23, R1

3.1 Introduction

There exist numerous macroeconomic approaches which explain the severity of unemployment at the national level. However, disparities in unemployment are not only observed among the countries but also among the regions within the same

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country. Treating unemployment on a more detailed level might lead to more reliable results. Moreover, the reduction of unemployment diversities between regions leads to desirable outcomes such as higher national product and lower inflation (Taylor 1996). The country benefits from more equal regional unemployment rates also because the reduction of disparities "lessens the adverse effect related to geographical concentrations of high unemployment and counteracts the downward spiral effect of economically depressed regions" (Elhorst 2003). Therefore, the issue of persistent regional inequalities between the local labor markets is widely investigated (e.g., Boeri 2000; Overman and Puga 2002; Bornhorst and Commander 2006; Huber 2007; Ferragina and Pastore 2008) as well as the issue of regional unemployment rates (see among others Bornhorst and Commander 2006; Newell and Pastore 2006; Jurajda and Terrell 2009; Marelli et al. 2012).

Decisions of labor market participants are not restricted by regional borders. Those in search of jobs also consider possibilities to move to other regions. On the other hand, firms' decisions on the location are dependent on situations in local labor markets. Bronars and Jansen (1987) established that a one-period shock in the local labor market has an impact on the neighboring regions, which are located up to 200 km away. Spatial distance costs might be the reason for the slow equilibrating mechanisms of labor markets and, thus, cause higher unemployment. Overman and Puga (2002) argue that the level of regional unemployment is linked much more to the neighboring regions than to other regions within the same country. They also conclude that divergence in regional unemployment rates might be the result of spatial polarization of economic activities due to economic integration. Pastore (2012) studies how structural changes and worker reallocation affect local unemployment rates. In addition, observed spatial dependence might serve as a proxy for unobserved omitted variables (Fingleton 1999). Therefore, spatial autocorrelation of unemployment has to be taken into account in the regression analysis. Ignoring spatially dependent variables in the regression model leads to biased and inefficient estimates, whereas ignoring spatial dependence in errors leads to unbiased but inefficient estimates. The existence of the upward bias in the coefficients was theoretically determined by Franzese and Hays (2007) and empirically shown by Lottmann (2012) for the estimation of unemployment.

The current paper analyzes the determinants of regional unemployment in Germany, taking into account spatial interactions between regions. We expect that regional distribution of unemployment is affected by the following determinants: employment growth, the cost of labor, the sectoral structure, age and educational structure of the population, regional GDP, and population density. We use panel data on 407 out of 413 German counties for the period from 2001 until 2009. In order to estimate the spatial panel data model, we employ two estimation techniques: a maximum likelihood estimation approach, developed specifically for spatial models, and the system generalized method of moments. We explore the differences in the determinants of unemployment for eastern and western regions of Germany. Furthermore, we investigate the differences in the spillover effects within eastern and western areas of Germany as well as between them.

One of the essential contributions to the spatial econometric analysis of unemployment was made by Molho (1995). Using cross-section data, he finds that inclusion of spatial spillover effects substantially reduces the spatial autocorrelation in residuals. He emphasizes that the spatial spillover effects are significant in adjustments to local demand shocks. Aragon et al. (2003) perform a search for the best spatial model specification for the unemployment rates in the Midi-Pyrenees region. After performing a set of LM tests, he claims that the best specification for the French data is a simple model with spatial dependence in errors. He finds that unemployment is more of disequilibrium nature. Cracolici et al. (2007) explores spatial dependence of unemployment in Italy, claiming that the best model contains spatially lagged dependent variable, which is in line with the Aragon's conclusion for French regions (Aragon et al. 2003). Cracolici finds that unemployment in Italy is more driven by the disequilibrium factors rather than by equilibrium ones; hence, unemployment disparities are mainly caused by labor demand factors. The results obtained by Niebuhr (2003) on spatial panel data models estimation, in which spatially lagged dependent variables are included and the disturbances have spatial structure, show that the European labor market experience has substantial spatial dependence. Basile et al. (2012) study the effect of interregional migration flows on the regional unemployment in Italy using spatial dynamic panel data models. They find that migration flows tend to magnify spatial disparities in unemployment rates. The essential contribution to the spatial analysis of regional unemployment in Germany is provided by Lottmann (2012). She also makes the first attempt to explore the differences between spatial interactions in West and East Germany by applying the models to eastern and western regions separately. She finds that "the spatial dynamic panel data model is the best model for the analysis of regional unemployment."

The contribution of the chapter is the following. The study makes an attempt to explore territorial differences in unemployment rates by applying extended specification developed by Demidova et al. (2013). It allows to analyze the spillover effects not only within East and West parts of Germany as it was made by Lottmann (2012) but also between western and eastern regions. We find that the unemployment is of both equilibrium and disequilibrium nature. It occurs that the unemployment in West Germany is more of disequilibrium nature, whereas the unemployment in East Germany is more of equilibrium nature. The analysis also reveals that the unemployment in East Germany affects both unemployment in West and East Germany. On the contrary, the unemployment in western regions impacts only on unemployment in West Germany.

The chapter is organized as follows. The next section reviews the theoretical explanation of the regional unemployment diversities. Section 3.3 describes the data set, the explanatory variables, and the spatial weights matrix. Section 3.4 describes the estimated models as well as the estimation methods, and Sect. 3.5 presents the results. Finally, Sect. 3.6 concludes.

3.2 Theory of Regional Unemployment Diversities

According to Marston (1985), the unemployment diversities have two origins: the equilibrium phenomenon and disequilibrium phenomenon. The disequilibrium view assumes that unemployment rate reaches its underlying mean only in the long run period since the adjustment can be sluggish. Hence, differences in unemployment rates will not vanish during a long period of time. The disequilibrium-based unemployment rate depends on the speed of adjustment between the regional labor markets. Thus, the migration processes are crucial to consider within this approach. The speed of adjustment can be affected both by labor supply and labor demand functions. Particularly, equalizing patterns are determined by the flexibility of wages, households' decisions on migration and labor force participation, and businesses locations (Aragon et al. 2003). The equilibrium view assumes that external shocks or economic disturbances in the labor market affect the unemployment rate for a short period of time, allowing it to converge back to its mean value. According to this approach, each region has its own underlying mean unemployment rate in the stable equilibrium. These equilibrium regional means are dependent on the groups of regional amenities, which restrain further migration processes between the regions. Different regional mean values can also indicate the differences in the regional industry occupation and wage differences.

The impact of some determining factors might be explained both through equilibrium and disequilibrium views. Nevertheless, we divide the set of explanatory factors into two groups. The factors generally reflect three main categories: labor demand, labor supply, and wage-setting factors. Elhorst (2003) also considers the division into predetermined and strictly exogenous explanatory factors. Predetermined variables can be replaced by other explanatory variables, which are, however, usually not available.

3.2.1 Unemployment of Disequilibrium Nature

A group of significant determinants of the unemployment rates are related to the demographic characteristics of the region. The birth rate positively influences the regional unemployment rate (Johnson and Kneebone 1991). Age structure of the population affects unemployment in the following way. A population with high share of young people leads to more severe unemployment problems (Hofler and Murphy 1989; Elhorst 1995). However, the share of elderly people does not affect the unemployment rate as severely as the share of young people (Partridge and Rickman 1995). In fact, birth rate is directly related to the age structure of the population: the high birth rate increases the share of young people and reduces the share of the older generation (Elhorst 2003). The disequilibrium effect of the age structure is based on the fact that young people are more likely to move to another region in comparison with old people, who are highly risk averse and have high opportunity costs (Aragon et al. 2003). Therefore, the adjustment mechanism works better when there are more young people in the labor force.

More educated people have greater opportunities to migrate because they are in higher demand in the labor market (McCormick and Sheppard 1992). They are also better informed about the economic conditions in the regions and thus are more willing to migrate. Hence, better education levels result in faster adjustment of the labor market (Aragon et al. 2003). Thus, regions with a big share of higher-educated people experience lower rates of unemployment.

The unemployment rate tends to be lower for urban regions. The matching process is in general faster in urban areas than in rural ones. Due to the better matching mechanism, it is easier to find jobs in urban regions. In addition, in those regions where the population density is higher the process of labor market adjustment is faster. This pattern is captured by Molho (1995) in a migration-based model.

The speed of adjustment is also determined by the magnitude of migration costs. A good indicator of costs of migration might be the structure of the housing market. Rising home prices increase costs of migration and therefore decrease the speed of adjustment. On the other hand, the housing market can also represent the equilibrium-based factor. Housing prices almost perfectly reflect costs of living. In equilibrium a region with low costs of living tends to have a higher unemployment rate since lower costs of living increase the real wage, which, in turn, positively affects the unemployment rate (Aragon et al. 2003).

High compensations for unemployment weaken incentives to search for jobs quickly or migrate, which slows down the adjustment process. The unemployment benefits can influence regional unemployment in the equilibrium state, and this case will be considered later. The effect of employment growth on unemployment is direct by construction. Employment growth is considered as the disequilibrium effect. In many studies, it is determined that employment growth affects unemployment (e.g., Burridge and Gordon 1981; Molho 1995). It can also affect the unemployment rates of the regions in the neighborhood.

Thus, the disequilibrium-based factors are mainly driven by the labor supply related characteristics. From the labor demand side, the reaction cannot be as fast as on the supply side since firms have higher costs of moving to other regions.

3.2.2 Unemployment of Equilibrium Nature

In one of the earliest empirical papers that investigated the unemployment within the equilibrium approach based on cross-section data, while analyzing the cross-sectional data, Marston (1985) finds that a higher probability of being unemployed is compensated by local regional benefits, including higher local wages, amenities, and higher unemployment benefits. These factors vary by region. If the labor market would work perfectly and the participants of the labor market from the demand and the supply sides would have the possibility to migrate freely, then the differences in the unemployment rates would disappear. The workers would migrate to the regions with higher demand, unless there are some factors, which attract people to live in the region of their current residence. The examples of these factors are the standards of living, climate, cultural activity, nature, and infrastructural development. Other relevant characteristics of the region include also housing conditions, crime severity, mortality, and air pollution (Burridge and Gordon 1981). The effect of amenities is also accounted for the migration-based models. An interesting approach is implemented by Molho (1995). He modeled migration flows with respect to unemployment, reverting the equation afterwards.

The relationship of the unemployment rate and the average wage is obvious. However, the direction of the dependency might seem surprising. In the equilibrium state, the expected income of a person is formed by the expected wage multiplied by the probability of being hired. This probability is typically measured as one minus the unemployment rate. Hence, assuming that expected income is equal across regions, a higher wage corresponds to a higher unemployment level ceteris paribus (Harris and Todaro 1970). Moreover, higher wages reduce labor demand. This fact confirms a positive dependency between the average wage and unemployment rate. However, most of the empirical studies do not confirm this effect: they find a negative or insignificant impact of wages on unemployment (Partridge and Rickman 1995; Molho 1995). It should be noted that nominal wages also reflect costs of living and housing prices.

The unemployment rates obviously differ between industries. Several sectors, such as textiles and metal manufacturing, are characterized by higher unemployment than, for example, services (Armstrong and Taylor 1988). Furthermore, the same industry might have different unemployment rates in different regions. Thus, the "industrial composition effects are a primary reason why labor demand and hence unemployment differ across regions" (Martin 1997). Krugman (1995) asserts that the impact of the industry divergence between regions reflects the influence of integration. Developing integration reduces transaction costs that in turn spurs regional specialization. Economies become less diversified, which makes them more sensitive to the external shocks. As a result, the higher intensity of economic fluctuations strengthens the variability in employment. Elhorst (2003) also affirms the importance of the sectoral structure for unemployment rates, explaining that regions, which specialize in poor economic sectors, tend to have higher rates of unemployment than those specializing in prosperous sectors, such as manufacturing or services.

One proxy for regional amenities can be the gross regional product. GDP per capita and the unemployment rate are negatively correlated, which, however, is not necessarily the case when exploring this dependence over time (Elhorst 2003). Another proxy might be population density, which is obviously evidence of regional attractiveness.

Thus, the equilibrium approach focuses on amenities, industrial structure, and costs of living, whereas the disequilibrium approach concentrates on the factors that influence the speed of adjustment. Although the equilibrium and disequilibrium approaches are quite different, a combination of factors from both approaches are used in most studies (e.g., Partridge and Rickman 1997; Aragon et al. 2003;

Cracolici et al. 2007; Lottmann 2012). Exploring both types of factors allows to decide whether the unemployment is more of equilibrium or disequilibrium nature. If the unemployment is of more equilibrium nature, then the attempts of the government to reduce regional differences are more useless than efficient because the government cannot reduce the long run unemployment rate (Marston 1985).

3.3 Data

3.3.1 Unemployment Rate and Its Determinants

The data on the majority of variables, used in the current study, are provided online by the Federal Statistical Office (Statistisches Bundesamt). Information about hourly average regional wages and gross regional products per capita are provided by the Statistical Office of Baden–Würtemberg (Arbeitskreis Volks-Wirtschaftliche Gesamtrechungen der Länder).

The definition of the unemployment rate used in this study corresponds to the latest one provided by the Federal Employment Office. The unemployment rates are calculated on a yearly basis for the whole period according to this latest official definition, although the definition changed during the investigated period. Following other studies, devoted to spatial analysis of employment, we use NUTS III level as it is considered to be the most meaningful regional division for labor market analysis.

The study performed utilizes data for the 2001–2009 period for 407 out of 413 German counties. The data for some counties are not included in the study due to district reforms. One was carried out in the federal state of Saxony–Anhalt and became effective as of July 2007. The other reform concerns the federal state of Saxony, which resulted in a reduced number of districts in August 2008. We aggregate the data according to these reforms, with exception of six counties of Saxony–Anhalt for which aggregation is not possible due to data unavailability.

Table 3.1 presents the summary statistics of the annual unemployment rates. Figure 3.1, as well as Tables 3.6 and 3.7 in the appendix, depicts separately summary statistics for Eastern and Western Germany. We observe a downward trend in average regional unemployment rates for the country as a whole. Unemployment rates in East Germany are generally higher than in West Germany.

According to the theory, unemployment can be driven by equilibrium and disequilibrium effects. In order to account for both effects, we construct a model that contains explanatory variables in accordance with both theories. Following Lottmann (2012), we use explanatory variables that consist of the following groups: disequilibrium effects, including demographic characteristics, and equilibrium effects, including market equilibrium effects and amenities of the regions.

In order to account for this disequilibrium effect, we include the employment growth rate. Obviously, we expect a negative impact of this variable on the unemployment rate. Demographic characteristics are represented by the share of young people in the population of ages from 15 to 65 (share of young population)

Table 3.1 Regional unemployment rates

Year	Min	1st Qu.	Mean	Median	3rd Qu.	Max	Std.dev.
2001	2.15	5.51	9.21	7.55	11.29	27.57	5.29
2002	2.70	6.15	9.75	8.11	11.36	28.67	5.28
2003	3.38	6.90	10.54	8.89	12.05	30.68	5.38
2004	3.19	6.95	10.56	8.96	12.27	31.14	5.37
2005	3.43	7.69	11.45	10.06	13.76	29.48	5.16
2006	2.92	6.78	10.58	9.38	12.72	28.16	4.93
2007	2.43	5.34	8.87	7.92	10.98	25.24	4.58
2008	1.96	4.32	7.59	6.53	9.67	23.18	4.16
2009	2.28	5.04	7.95	7.13	9.89	21.46	3.74

Summary statistics

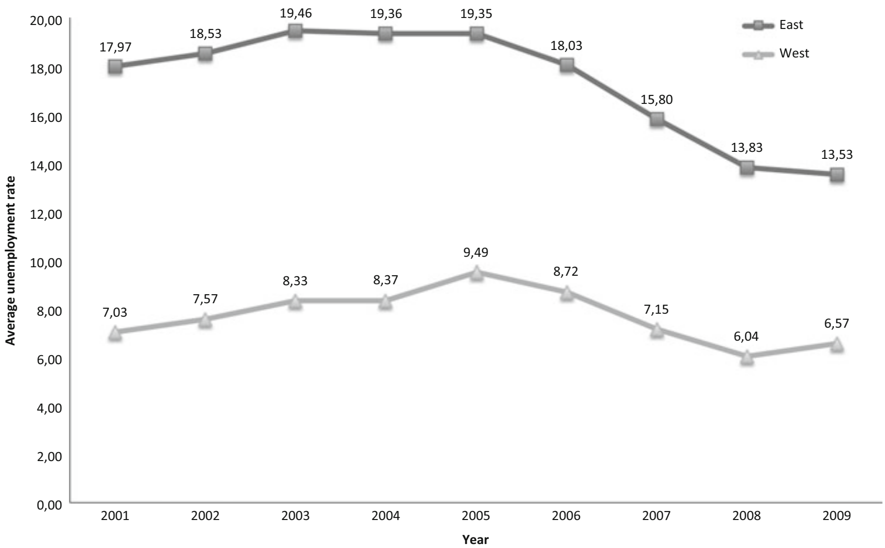

Fig. 3.1 Average unemployment rates for West and East Germany

and the share of old people in the population of ages from 15 to 65 (share of old population). Although the theory states that young people are more likely to migrate in order to find a job, we expect the variable *share of young population* to have the negative coefficient. As a rule, the younger population is characterized by higher unemployment rates since these people may still be in school. Molho (1995) finds that the proportion of elderly people (over 65) has a positive effect on the unemployment rate. Conversely, we expect a negative sign for the variable *share of old population* since we use the share of the 50–65 aged people in the labor force. Usually, people of these ages have permanent jobs and are unlikely to lose them due to a large number of factors, such as experience, commitment, etc. Educational levels characterizing human capital are included in our analysis: education without any professional training and education with a university degree.

As proxies for regional amenities, we use GDP per capita and population density (variables *GDR per capita* and *Density of population*). The higher the regional GDP, the more attractive is the region. Population density is often used as a proxy for regional amenities. It is also used as a disequilibrium factor because the density of the population spurs the matching processes in the labor market. On the other side, applicants living in regions with higher population densities require more time to collect necessary information about job opportunities (Partridge and Rickman 1995; Taylor and Bradley 1997). Hence, we expect the negative effect of GDP on unemployment and do not make any supposition of the impact of the population density.

With regard to the equilibrium approach, we consider the effect of the sectoral structure of the local labor market, which is the basic cause for regional unemployment diversities. We utilize employment shares of the agricultural, manufacturing, construction sectors, and sector of trade, hotels, restaurants, and transport. The significance of the industry structure is confirmed by many studies (e.g., Armstrong and Taylor 1993; Lottmann 2012). We expect positive signs for the agricultural sector and a negative sign for the other coefficients. We include the average hourly regional wage as an additional factor, as reflected in the equilibrium approach. According to the theory, we expect a positive sign of the coefficient.

3.3.2 Spatial Correlation

In order to account for spatial dependence in the regression model, we use a spatial weighting matrix that determines the intensity and the structure of the spatial dependence between regions exogenously. The intensity of the spatial interaction between region i and region j is represented by the element w_{ij}.

The problem of the choice of the best spatial matrix is still in the developing phase. There are several ways to define the spatial matrix. The simplest one is the binary continuity matrix. The elements of the matrix are equal to one if two regions share a border and zero otherwise. However, spatial matrices are often based on the distance functions. Niebuhr (2003) and Lottmann (2012) base their studies on distance decay functions. They use a negative exponential function of the product of two factors: the distance between the regional centers and the decay parameter.

In the current study, we use the inverse distance matrix, whose elements are simply constructed as the inverse values of the distance:

$$W = \begin{pmatrix} 0 & \frac{1}{d_{12}} & \cdots & \frac{1}{d_{1N}} \\ \frac{1}{d_{21}} & 0 & \cdots & \frac{1}{d_{2N}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{1}{d_{N1}} & \frac{1}{d_{N2}} & \cdots & 0. \end{pmatrix}$$

The straightforward inverse distance weighting (IDW) spatial technique is developed by Burrough and McDonnell (1998) and Anselin (2002). In the current study, we use the air (as a crow) distances between the regional centers. The spatial weights matrix is row-standardized for easier interpretation (e.g., Aragon et al. 2003; Niebuhr 2003; Lottmann 2012).

As a starting point for analysis, we calculate Moran's indexes for each year as most studies devoted to spatial analysis do. Moran's index is calculated in the following way (Moran 1950):

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \cdot \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(u_i - \bar{u})(u_j - \bar{u})}{\sum_{i=1}^{n}(u_i - \bar{u})^2}, \tag{3.1}$$

where u_i and u_j are unemployment rates in region i and j, respectively, $\bar{u}$ is the average rate of unemployment over n regions, w_{ij} is the element of the spatial weights matrix, which reflects the impact of region j on region i, and n is the total number of regions.

Moran's I takes values in the interval $[-1; 1]$, where the values, which are closer to 1, indicate high positive spatial correlation, and the values, which are closer to -1, indicate negative spatial correlation.

Determination of the significance of the Moran's I is based on the calculation of the statistic Z:

$$Z = \frac{I - E[I]}{sd(I)}, \tag{3.2}$$

where $E[I]$ denotes the average value and $sd(I)$ is the standard deviation. The null hypothesis is zero spatial autocorrelation (Moran's $I = 0$). The alternative hypothesis is the existence of spatial autocorrelation (Moran's $I > 0$ or Moran's $I < 0$). One can show that under the null hypothesis of zero spatial autocorrelation, the index is normally distributed for large samples (Sen 1976). Hence, the statistic is asymptotically standard normal under the null hypothesis. The performance of Moran's statistic for small samples is investigated by Anselin and Florax (1995). With the help of a simulation study, they find that it performs quite well. When calculating Moran's index, one should also assume that all trends in the data do not exist or are removed. Otherwise one might face a spurious dependence.

The calculated index shows significant positive spatial correlation (see Table 3.2). Spatial correlation in western regions is substantially higher than in eastern regions. Thus, significant spatial autocorrelation indices provide evidence of the spatial interactions between the regions, which have to be taken into account when analyzing the unemployment rates in the regression analysis.

Table 3.2 Spatial correlation indices for unemployment rates

Years	2001	2002	2003	2004	2005	2006	2007	2008	2009
Moran's spatial correlation index for unemployment rate									
Germany	0.249***	0.243***	0.237***	0.233***	0.235***	0.233***	0.240***	0.245***	0.231***
West	0.233***	0.211***	0.192***	0.193***	0.222***	0.236***	0.253***	0.275***	0.251***
East	0.038***	0.025**	0.033***	0.039***	0.026**	0.030**	0.052***	0.057***	0.028**

Note: ***, **, * indicate the values that are significant at 1%, 5% and 10% respectively

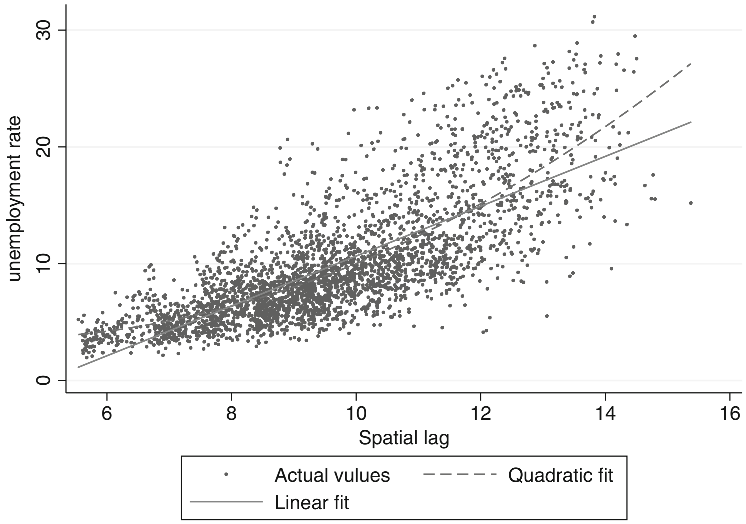

Fig. 3.2 Moran's plot

In order to visualize spatial dependence between the unemployment rates of different regions, one can plot Moran's scatter plot (see Fig. 3.2). The plot illustrates the dependence between the unemployment rate (Y) and the spatially weighted sum of unemployment rates of other regions (WY).

3.4 Spatial Econometric Modeling

3.4.1 Static and Dynamic Spatial Model

We consider panel models with fixed effects with a two-way error component. All the regressors vary over time. Time effects are included. There are different specifications that account for spatial autocorrelation. It should be noted that there exist three main types of spatial interactions within the model: endogenous interaction effects, exogenous interaction effects, and interaction effects among the error terms. In order to find the appropriate specification, Lottmann (2012) uses the LM statistics and tests five different hypothesis, using the approach of Debarsy and Ertur (2010).

First, we estimate the spatial autocorrelation (SAC) model, following Lottmann (2012) in the choice of the specification:

$$Y_t = \rho W Y_t + X_t \beta + \mu + \gamma_t \mathbb{1}_N + V_t, \quad V_t = \lambda W V_t + \epsilon_t, \quad t = 1, \ldots, T, \tag{3.3}$$

where Y_t is a $(N \times 1)$ vector of dependent variables, X_t is a $(N \times k)$ matrix of explanatory variables, μ is a $(N \times 1)$ vector of individual specific effects, and $\mathbb{1}_N$ is a $(n \times 1)$ vector of ones. γ_t represents time effects, and the elements of the disturbance term vector are assumed to be i.i.d. across i and t: $\epsilon_{it} \sim (0, \sigma^2)$.

W is assumed to be a nonnegative $(N \times N)$ exogenous spatial matrix. The diagonal elements of the matrix are zero by construction. Vector WY_t denotes endogenous spatial effect among the dependent variables. Vector WX_t denotes the exogenous interaction effect of the independent variables on the dependent variable. Vector WV_t represents the spatial dependence in the disturbances. The spatial coefficients of interest are the spatial autoregressive coefficient ρ and the spatial autocorrelation coefficient λ.

The method of estimation used for this equation is the maximum likelihood estimating procedure for spatial lag model (Anselin 1988), elaborated for the panel data case. However, this does not solve all the estimation problems. In the case of a small T and large N, one gets inconsistent estimates of the variance parameter when the model includes fixed individual specific effects and excludes fixed time effects. One also gets inconsistent estimates of the other parameters if the model includes both fixed individual and time effects. Even when both N and T are large, the distributions of the estimators of the parameters are not centered (Lee and Yu 2010a). Therefore, we use the maximum likelihood approach corrected for this bias by Lee and Yu (2010a,b). In order to avoid the inconsistency of the parameters, they propose a simple transformation. Instead of applying the within transformation, they suggest two orthogonal transformations in order to eliminate fixed effects and time effects. The joint significance of fixed individual effects of the model is tested by the likelihood ratio test.

3.4.2 Dynamic Spatial Model

As it was determined earlier (e.g., Niebuhr 2003; Lottmann 2012), a dynamic approach is more appropriate for investigating the labor market. Hence, we estimate the spatial autoregression (SAR) model with dynamic lag of the dependent variable.

$$Y_t = \tau Y_{t-1} + \rho W Y_t + X_t \beta + \mu + \gamma_t \mathbb{1}_N + \epsilon_t, \qquad t = 1, \ldots, T, \tag{3.4}$$

where Y_{t-1} is the lag of the dependent variable. The elements of the disturbance term vector are assumed to be i.i.d.: $\epsilon_{it} \sim (0, \sigma^2)$. All other notations are the same as in previous model.

The full model, which contains both a lagged dependent variable and spatial correlation in errors, cannot be estimated due to the identification problem (Anselin et al. 2008). It should be first checked whether it is better to include a spatially lagged dependent variable or to include spatial dependence in disturbances (Florax and Folmer 1992). To test for the significance of spatial dependence in disturbances, Aragon et al. (2003) use a Lagrange multiplier test proposed by Burridge. If the test results show that a spatially lagged dependent variable should be included, one should further test whether the spatially lagged independent variables should also be taken into consideration. We omit these testing procedures and use the result of the specification choice, made by Lottmann (2012).

Three methods have been adopted to estimate dynamic spatial panel data models. We dwell on the maximum likelihood (ML) estimation and the generalized method of moments based on instrumental variables (IV/GMM). We apply the maximum likelihood estimator constructed firstly by Yu et al. (2008) and later developed by Lee and Yu (2010a) to correct for the discussed above bias (BCLSDV estimator). This BCLSDV estimator can also be used when either Y_{t-1} or WY_{t-1} is not included in the specification (Elhorst 2012). Further, we implement the instrumental variables estimation approach, built on the estimation procedures developed for dynamic panel data without spatial interactions (Arellano and Bond 1991; Blundell and Bond 1998).

Elhorst (2010) finds that the difference GMM estimation leads to the biased estimates, especially for the coefficient ρ. An appropriate GMM is proposed by Lee and Yu (2010a). The estimator is consistent even when T is small and N is large. Another way to get consistent estimates by the GMM estimation is to use the system GMM estimation approach (Kukenova and Monteiro 2009). Their study finds that the system GMM approach is appropriate because the bias, determined by Lee and Yu (2010a), diminishes significantly and can even be ignored. Furthermore, the GMM approach has an additional advantage to instrument endogenous regressors. We consider both ML and system GMM approaches in order to compare the results obtained. We include the second lag in the model due to the second order correlation in the disturbances, detected by the Arellano–Bond test after GMM estimation.

3.4.3 Direct and Indirect Effects

In the case of the linear regression model, the interpretation is straightforward. As we have linearity in the parameters and the observations are assumed to be independent, the parameter can be interpreted as the partial derivative of the dependent variable with respect to the independent variable. When we account for spatial interactions in the regression models, the interpretation needs more proper consideration (Anselin and Le Gallo 2006). To find the proper way to interpret parameters of the spatial model, we consider a simple cross-section spatial model with spatially lagged dependent variable:

$$y = \rho W y + X\beta + \mathbb{1}_N \alpha + \epsilon, \tag{3.5}$$

where y is a $(N \times 1)$ vector of the dependent variable, W is a $(N \times N)$ spatial weights matrix, X is a $(N \times K)$ matrix of K independent variables, and disturbances are assumed to be i.i.d.: $\epsilon \sim (0, \sigma^2 I_N)$.

We can rewrite the model assuming that the matrix $(I - \rho W)$ is invertible:

$$\begin{aligned}(I - \rho W)y &= X\beta + \mathbb{1}_N\alpha + \epsilon, \\ y &= (I - \rho W)^{-1}X\beta + (I - \rho W)^{-1}\mathbb{1}_N\alpha + (I - \rho W)^{-1}\epsilon. \end{aligned} \tag{3.6}$$

If we denote the matrix $(I - \rho W)^{-1}I_N\beta_r$ as the matrix $S_r(w)$ (LeSage and Pace 2009), we can rewrite Eq. (3.6) in the following way:

$$y = \sum_{r=1}^{k} S_r(w)x_r + (I - \rho W)^{-1}\mathbb{1}_N\alpha + (I - \rho W)^{-1}\epsilon. \tag{3.7}$$

The derivative of y_i with respect to x_{jr} is represented by the ij-th element of the matrix $S_r(W)$ and corresponds to the indirect effect:

$$\frac{\partial y_i}{\partial x_{jr}} = S_r(W)_{ij}, \tag{3.8}$$

i.e., the change in the explanatory variable for region j might affect the dependent variable of any other region i as the derivative of y_i with respect to x_{jr} might not be equal to zero. The derivative of y_i with respect to x_{ir} is represented by the ii-th element of the matrix $S_r(W)$ and corresponds to the direct effect:

$$\frac{\partial y_i}{\partial x_{ir}} = S_r(W)_{ii}. \tag{3.9}$$

In case of dynamic spatial model matrix, $S_r(w)$ is equal to $((1-\tau)\,I - \rho W)^{-1}\,I_N\beta_r$, where τ is the coefficient of the dynamic lag. The matrix allows to get long run direct and indirect effects.

The direct effect (M_{direct}) is defined as the average of the diagonal elements of the matrix $S_r(W)$. The indirect effect (M_{direct}) is defined as the average of the row sums of the non-diagonal elements of the matrix $S_r(W)$ (LeSage and Pace 2009):

$$\begin{aligned} M(r)_{\text{direct}} &= N^{-1}tr(S_r(W)) \\ M(r)_{\text{indirect}} &= N^{-1}\mathbb{1}_N^{\top}S_r(W)\mathbb{1}_N - N^{-1}tr(S_r(W)). \end{aligned} \tag{3.10}$$

LeSage and Pace (2009) propose the approximation in order to avoid the inversion of the matrix $(I - \rho W)^{-1}$. Assuming that $\mid \rho \mid < 1$, $(I - \rho W)^{-1}$ can be rewritten as

$$(I - \rho W)^{-1} = I_N + \rho W + \rho^2 W^2 + \rho^3 W^3 + \dots. \tag{3.11}$$

The direct and indirect effects are calculated, fulfilling the requirement that the approximation is considered up to the large enough power. We calculate the direct and indirect effects for the proposed SAC model and long run direct and indirect effects for the SAR model, estimated by ML.

3.4.4 Estimating Spillover Effects Between East and West

To analyze the differences of the spillover effects between the Western and Eastern parts of Germany, Lottmann (2012) estimates the spatial static and dynamic models for both parts separately. Although this approach allows to investigate the differences between the impacts of the explanatory variables of East and West, it does not allow to investigate the spillover effects of the two groups of counties on each other. To not only identify the possible differences in the spatial spillover effects within the eastern and western regions but to also account for the spatial interactions between them, a special approach was developed for Russian data (Demidova et al. 2013). We implement this approach for the German data by applying the following specification:

$$\begin{pmatrix} Y_t^w \\ Y_t^e \end{pmatrix} = \tau \begin{pmatrix} Y_{t-1}^w \\ Y_{t-1}^e \end{pmatrix} + \begin{pmatrix} \rho_{ww} W_{ww} & \rho_{we} W_{we} \\ \rho_{ew} W_{ew} & \rho_{ee} W_{ee} \end{pmatrix} \begin{pmatrix} Y_t^w \\ Y_t^e \end{pmatrix} + \begin{pmatrix} X_t^w \beta_w \\ X_t^e \beta_e \end{pmatrix} + \gamma_t \mathbb{1}_N + \mu + \epsilon_t, \tag{3.12}$$

$$t = 1, \ldots, T,$$

where Y_t^w and Y_t^e denote $(N^w \times 1)$ and $(N^e \times 1)$ vectors correspondingly, the subscript $(t-1)$ denotes the lagged value of a vector, X_t^w and X_t^e are $(N^w \times K)$ and $(N^e \times K)$ matrices of the explanatory variables, μ is an $(N \times 1)$ vector of individual effects, $\mathbb{1}_N$ is a vector of ones, and ϵ_t is a vector of i.i.d. disturbance terms with zero mean and constant variance σ^2.

The spatial weights matrix is decomposed into four parts:

$$W = \begin{pmatrix} W_{ww} & 0 \\ 0 & 0 \end{pmatrix} + \begin{pmatrix} 0 & W_{we} \\ 0 & 0 \end{pmatrix} + \begin{pmatrix} 0 & 0 \\ W_{ew} & 0 \end{pmatrix} + \begin{pmatrix} 0 & 0 \\ 0 & W_{ee} \end{pmatrix}. \tag{3.13}$$

Here, the coefficients ρ_{we} and ρ_{ew} reflect the influence of the eastern counties on the western ones and vice versa. Coefficients ρ_{ww} and ρ_{ee} represent the spatial interaction effects within the Western and Eastern parts of Germany. The impacts of the independent variables may differ for western and eastern regions. Therefore, the variables are doubled in a specific way (Demidova et al. 2013), for example:

$$\text{Hourly wage (west)}_{it} = \begin{cases} \text{hourly wage}_{it}, \text{if } i \text{ denotes west region} \\ 0, \text{if } i \text{ denotes east region} \end{cases}$$

$$\text{Hourly wage (east)}_{it} = \begin{cases} 0, \text{if } i \text{ denotes west region} \\ \text{hourly wage}_{it}, \text{if } i \text{ denotes east region.} \end{cases}$$

We use the system GMM estimation technique to estimate this model. Using Wald tests, we verify the hypothesis that the coefficient of a particular variable for eastern regions is the same coefficient as for the western regions, for example $H : \beta_{\text{ehwage}} = \beta_{\text{whwage}}$. If the hypothesis cannot be rejected, then we include the variable *Hourly wage* instead of two variables *Hourly wage (west)* and *Hourly wage (east)*.

3.5 Results

3.5.1 Results of ML Estimation

Similarly to Lottmann (2012), we find that the dynamic spatial model is more appropriate using the information criteria (BIC), presuming that BIC is a better criteria for picking the best model (Haughton et al. 1997).

The direct effects are similar to the coefficients but are not equivalent. They lead to the same conclusions as the main coefficient estimates (see Table 3.3). However, for the exact interpretations about the explanatory variables, one has to employ direct effects. Table 3.4 reports the direct and indirect effects for both the static and the dynamic models. The estimates of the direct effects primarily have the expected sign. The influence of employment growth on the unemployment rate is negative, as we expected. The influence is stronger when we consider the dynamic model. The cost of labor, measured as the average regional hourly wage, affects the unemployment positively. This result confirms the theory (Harris and Todaro 1970). The shares of the persons employed in the agricultural sector affects the unemployment positively. In fact, this variable might capture the effect of the rural-state dummy variable, which can be included in the regression. Rural areas, where the population is primarily employed in the agricultural sector, are characterized by a higher level of unemployment. The share of the persons employed in the prosperous production industry has a negative impact on the regional unemployment. A surprising result is that the share of people employed in the construction industry increases regional unemployment. The result is counterintuitive since regions, specializing in growing industries such as construction, seem to have lower unemployment. The influence of the share of young people is positive, which is not surprising since most the

Table 3.3 SAC and SAR models

	(Model (3.3)) Unemployment		(Model (3.4)) Unemployment	
Main				
Employment growth	−0.0807***	(−7.08)	−0.203***	(−24.32)
Hourly wage	0.125***	(4.64)	0.127***	(6.06)
Agricultural sector	22.64***	(5.09)	41.58***	(9.52)
Production industry	−9.329***	(−6.84)	−4.459***	(−3.47)
Construction	−5.980*	(−1.97)	14.52***	(5.42)
Trade, hotels and restaurants, transport	2.456	(1.47)	3.360*	(2.02)
Share of young population	28.09***	(13.94)	16.64***	(10.16)
Share of old population	−22.71***	(−11.20)	−12.05***	(−6.99)
Share of employed persons without professional education	−8.860***	(−3.79)	7.274***	(3.70)
Share of employed persons with a university degree	13.05***	(3.70)	32.67***	(9.92)
Population density	−0.00249***	(−4.03)	−0.00234***	(−3.64)
GDP per capita	−0.0000349***	(−4.41)	−0.0000274***	(−3.76)
$\text{Unemployment}_{t-1}$			0.399***	(33.65)
Spatial				
ρ	0.935***	(45.88)	0.565***	(36.90)
λ	0.923***	(41.24)		
Variance				
σ_e^2	0.333***	(47.94)	0.247***	(45.39)
Observations	3,663		3,256	
AIC	6,121.9		4,419.5	
BIC	6,438.5		4,730.0	

t statistics in parentheses
$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

students receive their education before they turn 25 and do not have permanent jobs. The impact of the share of old workers approves our expectations that older workers experience less unemployment as they usually have permanent jobs and are unlikely to change it. Furthermore, it is unlikely that they will lose their job, which is a sign of low discrimination of older workers. Considering the dynamic model, we find that the share of persons without professional education increases unemployment, which is intuitively straightforward. However, an even larger positive effect is observed for the share of the persons with university education. A similar result for the share of workers with only vocational education was obtained by Lottmann (2012).

The gross regional product negatively affects regional unemployment, as we expected. Population density influences regional unemployment negatively as well. Interestingly, for different variables characterizing the attractiveness of the region (the magnitude of the public debts, number of business registrations in the region),

Table 3.4 Direct and indirect effects

	(Model (3.3)) Unemployment		(Model (3.4)) Unemployment	
Direct				
Employment growth	−0.0843***	(−8.34)	−0.203***	(−22.46)
Hourly wage	0.132***	(4.14)	0.128***	(5.62)
Agricultural sector	23.86***	(4.78)	41.76***	(9.86)
Production industry	−9.725***	(−6.91)	−4.201***	(−3.41)
Construction	−5.604	(−1.90)	15.23***	(5.58)
Trade, hotels and restaurants, transport	2.930	(1.69)	3.534*	(2.03)
Share of young population	29.20***	(13.39)	16.63***	(10.31)
Share of old population	−23.72***	(−10.86)	−12.21***	(−7.45)
Share of employed persons without professional education	−9.306***	(−3.91)	7.030**	(3.24)
Share of employed persons with a university degree	13.54***	(3.52)	32.90***	(9.56)
Population density	−0.00258***	(−4.10)	−0.00243***	(−3.92)
GDP per capita	−0.0000370***	(−4.43)	−0.0000278***	(−3.65)
Indirect				
Employment growth	−1.361	(−1.84)	−0.261***	(−22.79)
Hourly wage	2.214	(1.44)	0.166***	(4.96)
Agricultural sector	384.2	(1.74)	53.83***	(7.94)
Industrial sector	−159.4	(−1.58)	−5.398***	(−3.40)
Construction	−90.78	(−1.30)	19.68***	(4.76)
Trade, hotels and restaurants, transport	46.63	(1.18)	4.554*	(2.03)
Share of young population	471.3	(1.89)	21.45***	(7.70)
Share of old population	−383.0	(−1.87)	−15.68***	(−7.96)
Share of employed persons without professional education	−150.6	(−1.72)	9.071**	(3.10)
Share of employed persons with a university degree	225.0	(1.37)	42.42***	(7.59)
Population density	−0.0420	(−1.62)	−0.00313***	(−3.73)
GDP per capita	−0.000622	(−1.41)	−0.0000357***	(−3.58)
Observations	3,663		3,256	

SAC and SAR models
t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Lottmann (2012) gets non-expected results. Therefore, population density and gross regional product might be better proxies for the regional amenities than the number of new registered firms or the average number of tourists' stays per night. Hence, our model indicates that the unemployment is of both equilibrium and disequilibrium nature.

The indirect effects are significant only for the dynamic model. This shows that the impact of the change in the unemployment rate of one region on another can be captured only by the dynamic model. This confirms the fact that changes in unemployment in the neighboring regions influence the labor market of the explored region with a time lag. People do not immediately react to the local shocks. Their decisions to migrate in order to find a new job usually take some time. Firms' reaction could be even longer as they have higher transaction costs and have to more properly assess possible benefits and costs.

Indirect effects, also known as spatial spillover effects, have the same sign as the direct effects. However, indirect effects are actually higher than direct effects. This finding reveals the fact that changes in explanatory variables of other regions are more important than the changes in own characteristics. This brings us to the conclusion that laws and reforms aiming to reduce unemployment rate in one region have to consider not only the problem of the region but also in the neighboring regions.

The coefficients that characterize the spatial interactions (ρ and λ) are significant and positive. They are close to those obtained in the previous study for the static model ($\rho = 0.9$ versus $\rho = 0.8$ obtained by Lottmann (2012), and $\lambda = 0.9$ versus $\lambda = 0.7$). The SAR coefficient in the dynamic model differs more substantially ($\rho = 0.56$ versus $\rho = 0.88$) due to the different specifications. Lottmann (2012) accounts for the combined effect of the spatial lag and the dynamic lag. The coefficient of this combined effect is negative and significant, which explains the higher value of the spatial autoregressive coefficient ρ. The positive and significant spatial coefficients confirm the hypothesis of the spatial influence of the neighbor districts on the regional unemployment.

We repeat the estimation of the static and dynamic models for the Eastern and Western parts of Germany separately, following Lottmann (2012) (Tables 3.8 and 3.9 in the appendix), assuming that the coefficients of the explanatory variables differ between the West and East. This estimation allows to explore spillover effects within separate parts of the country. Most of the coefficients appear to be substantially different for West and East Germany. The negative impact of employment growth is slightly higher for East Germany. Among the industry variables, only the share of people employed in the agricultural sector and in manufacturing are significant for the West, and the share of people employed in agricultural sector is significant for the East. The share of young people becomes insignificant for the East. Interestingly, the education level stays significant only for the West part. The GDP stays significant only for the Eastern part of Germany. Population density loses its significance after the separation. Thus, some factors of the equilibrium approach (*GDP per capita, population density, construction, sector trade, hotels and restaurants, transport*) lose their significance for West Germany, whereas for East Germany there is a loss in significance primarily for the factors of disequilibrium approach (*share of young population, share of employed persons without professional education, share of employed persons with a university degree*). Therefore, unemployment in West Germany seems to be more of disequilibrium nature, and the unemployment in East Germany is more of equilibrium nature.

The spatial coefficients are significant for both parts of Germany. The spatial autocorrelation coefficient (λ) and the spatial autoregressive (ρ) are higher for West Germany in the static model. The spatial autoregressive coefficient in the dynamic model is also higher for West Germany. Thus, the spatial dependence is stronger for West Germany.

3.5.2 *Differences and Spillover Effects Between East and West*

Previously, we explore the spatial relationships within the Western and Eastern areas of Germany. The system GMM estimation of model (3.12) allows to explore the spatial effects of West unemployment on East and vice versa. We obtained significant coefficients ρ_{ee}, ρ_{ww}, and ρ_{we} (see Table 3.5). This means that the unemployment of the eastern regions influences both the unemployment in the West part and in the East part of Germany, whereas the unemployment of Western regions affects only its own unemployment. We obtained the significant spatial dependence in unemployment within the Western and Eastern regions while estimating the models separately by ML approach. Thus, if the unemployment rate reduces in one eastern region, the decrease in the unemployment rates occurs also in other eastern and western regions. When the unemployment rate changes in one western region, it leads to the similar changes in other western regions, but not in eastern ones. This one-direction spatial effect of the Eastern unemployment on the western regions is intuitively clear. Eastern regions suffer from more severe unemployment rates in general, which results in the bigger migration flows from East to West Germany.

Among the explanatory variables hourly wage, employment growth, commuters, GDP per capita, and spatial lags are considered as endogenous. Variables which indicate sectoral structure of a region and number of new firms registered are exogenous. Predetermined variables are unemployment rates in periods $t-1$ and $t-2$. From the results, we can conclude that the hourly wage influences significantly unemployment only in East Germany. The employment growth determines the unemployment only in western regions. Interestingly, the share of the people employed in the construction industry positively affects the unemployment rate only in eastern regions. The influence of the share of people with only school education is the same for both parts of Germany. It increases the rate of unemployment as it was previously determined. The regional GDP per capita remains significant and negative only for the East Germany. It is to be noted that the amenities (number of new firms registered and number of commuters), previously determined as insignificant for the whole country, become significant for East Germany. The number of commuters has a positive impact on the unemployment level, whereas the number of new firms negatively affects the rates.

Table 3.5 Dynamic model for West and East

	Model (3.12)	
$\text{Unemployment}_{t-1}$	0.795***	(12.58)
$\text{Unemployment}_{t-2}$	−0.113	(−1.83)
ρ_{ww}	0.548*	(2.44)
ρ_{ee}	0.623***	(3.62)
ρ_{ew}	0.222	(0.72)
ρ_{we}	0.591***	(4.50)
Hourly wage (west)	0.0000341	(0.40)
Employment growth (west)	−0.225***	(−4.68)
Agricultural sector	20.49	(1.24)
Production industry	−12.68***	(−3.42)
Construction (west)	−8.687	(−0.45)
Trade, hotels and restaurants, transport	3.379	(0.47)
Share of employed persons without professional education	25.73***	(3.60)
GDP per capita (west)	0.0000546	(1.34)
Commuters (west)	−0.0000117	(−0.70)
Number of new firms registered (west)	0.000130	(0.96)
Hourly wage (east)	0.000431*	(2.07)
Employment growth (east)	0.00311	(0.04)
Construction (east)	82.80**	(3.29)
GDP per capita (east)	−0.000554**	(−2.62)
Commuters (east)	0.000214***	(3.35)
Number of new firms registered (east)	−0.000565*	(−2.08)
Year dummy 2003	−1.351***	(−3.65)
Year dummy 2004	−1.683***	(−5.04)
Year dummy 2005	−0.957	(−1.87)
Year dummy 2006	−1.673***	(−4.34)
Year dummy 2007	−1.340***	(−7.23)
Year dummy 2008	−0.562***	(−3.45)
Constant	−6.909*	(−2.06)
Observations	2,749	

GMM estimation
t statistics in parentheses
$^{*}\,p < 0.05$, $^{**}\,p < 0.01$, $^{***}\,p < 0.001$

3.6 Conclusions

The current study investigates the determinants of unemployment in Germany with the help of spatial panel data models. We base analysis on a combined set of factors according to the equilibrium and the disequilibrium theory of regional unemployment diversities. Among the determinants that affect regional unemployment are employment growth, the cost of labor, the sectoral structure, age and educational structure of the population, and regional amenities (measured with the help of regional GDP and population density). In order to account for possible spatial interactions between regions, in the regressions we use spatial weighting matrix of the inverse distances. We estimate the static and the dynamic models by the maximum likelihood estimation approach, developed by Anselin (1988) and elaborated by Lee and Yu (2010a,b). In order to get proper interpretation, we compute the direct and indirect effects, proposed by LeSage and Pace (2009). We also implement the system generalized method of moments estimation for the dynamic model. We analyze the spillover effects in unemployment within West and East Germany by estimating the spatial models for the East and West separately, based on the ML approach. We investigate the spillover effects in unemployment not only within but also between the West and East parts of Germany by implementing the special specification, developed by Demidova et al. (2013).

We find that unemployment in Germany is of both equilibrium and disequilibrium nature, revealing appropriate proxies for the regional amenities (regional gross product per capita and population density). The spatial dependencies are significant both for the static and the dynamic spatial panel data models. In line with the results obtained by Lottmann (2012), we find the dynamic spatial model more appropriate for investigating the regional unemployment rates. We find that unemployment in West Germany is more of disequilibrium nature, whereas the unemployment in East Germany is more of equilibrium nature. The spatial relationship is stronger for West Germany. Furthermore, the unemployment of the Eastern regions influences both the unemployment in the West part and in the East part of Germany, whereas the unemployment in West Germany affects only its own unemployment.

Our findings lead to the following conclusions for the policy measures in the labor markets. Firstly, policy measures, devoted to the reduction of regional unemployment, should take into account the unemployment in the neighboring regions more seriously than the unemployment of the region itself. Secondly, as unemployment is of both equilibrium and disequilibrium nature, policy is not able to eliminate the unemployment completely. However, policy makers can still manipulate the factors of the disequilibrium view in order to reduce inequality in unemployment rates. Thirdly, policy makers should propose different policies for West and East Germany since they are determined by different sets of factors. Finally, it is important to take into account that unemployment rates in West Germany do not influence the unemployment rates in East Germany, whereas unemployment in East German affects both areas of the country.

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Appendix

See Tables 3.6, 3.7, 3.8 and 3.9.

Table 3.6 Unemployment in East Germany

Year	Min	1st Qu.	Mean	Median	3rd Qu.	Max	Std. dev.
2001	7.84	14.76	17.97	18.10	20.98	27.57	4.24
2002	8.50	15.40	18.53	18.37	21.55	28.67	4.31
2003	9.20	16.27	19.46	19.29	23.16	30.68	4.57
2004	8.91	16.21	19.36	18.89	22.52	31.14	4.78
2005	9.57	15.95	19.35	19.14	22.50	29.48	4.53
2006	8.43	14.75	18.03	17.62	20.76	28.16	4.42
2007	7.00	12.66	15.80	15.48	18.41	25.24	4.09
2008	5.79	11.03	13.83	13.10	16.49	23.18	3.68
2009	5.77	11.15	13.53	12.88	15.94	21.46	3.21

Summary statistics

Table 3.7 Unemployment in West Germany

Year	Min	1st Qu.	Mean	Median	3rd Qu.	Max	Std. dev.
2001	2.15	4.99	7.03	6.78	8.45	15.46	2.58
2002	2.70	5.59	7.57	7.43	9.12	15.71	2.51
2003	3.38	6.36	8.33	8.11	9.87	16.33	2.50
2004	3.19	6.39	8.37	8.17	9.97	16.80	2.52
2005	3.43	7.10	9.49	9.23	11.38	20.91	2.97
2006	2.92	6.35	8.72	8.41	10.69	19.02	2.88
2007	2.43	4.98	7.15	6.71	8.80	16.46	2.67
2008	1.96	4.05	6.04	5.57	7.64	14.83	2.48
2009	2.28	4.76	6.57	6.21	7.93	14.59	2.30

Summary statistics

Table 3.8 SAC and SAR models for West

	(Model (3.3)) Unemployment		(Model (3.4)) Unemployment	
Employment growth	−0.0930***	(−7.08)	−0.179***	(−19.05)
Hourly wage	0.0852***	(3.51)	0.0977***	(4.78)
Agricultural sector	23.60***	(4.66)	46.09***	(9.29)
Production industry	−8.780***	(−6.65)	−4.715***	(−3.68)
Construction	−2.100	(−0.58)	2.416	(0.72)

(continued)

Table 3.8 (continued)

	(Model (3.3)) Unemployment		(Model (3.4)) Unemployment	
Trade, hotels and restaurants, transport	0.852	(0.52)	1.636	(0.98)
Share of young population	−9.392*	(−2.37)	−16.18***	(−5.04)
Share of old population	−32.31***	(−14.23)	−13.06***	(−6.76)
Share of employed persons without professional education	−6.268**	(−2.81)	5.305**	(2.61)
Share of employed persons with a university degree	7.625*	(2.04)	30.23***	(8.89)
Population density	−0.00350***	(−3.98)	−0.00211*	(−2.52)
GDP per capita	−0.0000189*	(−2.50)	−0.0000125	(−1.74)
$\text{Unemployment}_{t-1}$			0.347***	(27.79)
Spatial				
ρ	0.889***	(27.44)	0.660***	(41.16)
λ	0.899***	(29.28)		
Variance				
σ_e^2	0.253***	(42.85)	0.197***	(40.62)
Observations	2,934		2,608	
AIC	4,125.5		2,971.2	
BIC	4,430.7		3,270.3	

t statistics in parentheses
$^{*} p < 0.05$, $^{**} p < 0.01$, $^{***} p < 0.001$

Table 3.9 SAC and SAR models for East

	(Model (3.3)) Unemployment		(Model (3.4)) Unemployment	
Employment growth	−0.0461	(−1.91)	−0.216***	(−12.10)
Hourly wage	0.395***	(3.53)	0.554***	(6.49)
Agricultural sector	18.11	(1.94)	28.94***	(3.41)
Production industry	−10.11*	(−2.36)	−7.193	(−1.86)
Construction	−20.07**	(−2.84)	12.15	(1.91)
Trade, hotels and restaurants, transport	3.924	(0.78)	3.668	(0.78)
Share of young population	13.30	(1.34)	2.549	(0.29)
Share of old population	−29.37***	(−4.74)	−24.30***	(−4.49)
Share of employed persons without professional education	1.553	(0.17)	10.69	(1.40)
Share of employed persons with a university degree	−10.21	(−1.00)	−0.389	(−0.04)

(continued)

Table 3.9 (continued)

	(Model (3.3)) Unemployment		(Model (3.4)) Unemployment	
Population density	−0.00176	(−1.61)	−0.00179	(−1.64)
GDP per capita	−0.000177***	(−6.68)	−0.0000925***	(−4.11)
$\text{Unemployment}_{t-1}$			0.540***	(19.79)
Spatial				
ρ	0.737***	(14.46)	0.382***	(9.21)
λ	0.434*	(2.42)		
Variance				
σ_e^2	0.563***	(21.38)	0.344***	(20.25)
Observations	729		648	
AIC	1,686.4		1,176.1	
BIC	1,920.6		1,404.3	

t statistics in parentheses
$^{*} p < 0.05$, $^{**} p < 0.01$, $^{***} p < 0.001$

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Chapter 4
Compensating Wage Differentials Across Russian Regions

Aleksey Oshchepkov

Abstract In this chapter, we provide evidence on compensating differentials in the labor market from the largest transition economy, Russia. Using the NOBUS micro-data and a methodology based on the estimation of the wage equation augmented by aggregate regional characteristics, we show that wage differentials across Russian regions have a compensative nature. Russian workers receive wage compensations for living in regions with a higher price level and worse nonpecuniary characteristics, such as a relatively low life expectancy, a high level of air pollution, poor medical services, a colder climate, and a higher unemployment level. These compensations are not associated with the existing government system of compensating wage coefficients. After adjusting for regional amenities and disamenities, regional wages become positively correlated with interregional migration flows. According to our estimates, wage compensations along with differences in employment composition are able to account for about three-fourths of the observed variation in wages across Russian regions.

Keywords Compensating differentials • Regional wages • Migration • Russia

JEL Classification J3, J6, P2, R2

4.1 Introduction

Market economies tend to generate compensating wage differentials; there are a lot of examples when workers receive wage supplements for working at worse jobs conditions (Rosen 1986). One of such examples is wage compensation for worse living conditions in some cities of a country. There is ample evidence from the US labor market that workers receive compensating differentials for living in cities with worse conditions (e.g., Roback 1982, 1988; Blomquist et al. 1988; Beeson 1991; Dumond et al. 1999; Costa and Kahn 2003).

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However, evidence on compensating wage differentials across cities or regions out of the USA is scarce. In the EU, one of a few known to us attempts to detect compensating wage differentials across cities is the study of Braakman (2009) for Germany. Applying the popular in the US studies approach, the author tried to find wage compensations for high crime levels in German cities, but did not receive expected results. He notes two possible reasons for this. First, German labor market is heavily institutionalized which may prevent adjustment of wages to local amenities and disamenities. Second, Germany is much more homogeneous than the USA regarding crime rates.

Surprisingly, more comprehensive evidence on compensating wage differentials across cities comes not from a mature market economy, but rather from a transition economy, Russia. Berger et al. (2008) argue that a Roback-style equilibrium model of compensating differentials may be applied to the Russian case. Similar to studies on the US cities, they estimate the size of compensating differentials for city amenities and disamenities generated in the labor and housing markets and then construct quality of life indices for Russian cities.

Indeed, although Russia is not a mature market economy, there are some factors, which support the functioning of the compensating mechanism in the country's labor market. First of all, Russia is a very large country, where environmental conditions and living costs vary significantly across cities and regions. Even under a planned economy, when the government could force people to settle in locations with worse living conditions or use some non-monetary mechanisms to attract people to such locations, a system of wage supplements existed. This suggests the compensating principle is not entirely new for Russia.

In the transition period, with the almost complete removal of migration regulation, people started to choose locations maximizing their utility functions, like in market economies. Two explicit trends in internal migration were observed in 1990s and early 2000s: migration from the eastern to the western part of the country, the so-called "western drift," and migration out of the Russian North. The main reasons for these migration flows were price liberalization and the drastic weakening of regional employment and equalizing policies. As a result, the population faced rising real living costs that were not compensated by income growth, in addition to a worsening of living conditions (Heleniak 1999; Mkrtchian 2003, 2005; Ryasantcev 2005; Karachurina 2007). Thus, it may be expected that the importance of the monetary compensating mechanism has only increased during transition.

Another factor favoring an effective functioning of wage compensating mechanism in Russia is the high flexibility of wages, in contrast to mature economies including Germany and even the USA. This flexibility is achieved in several ways. One of them is considerable variable fraction of total wage payments, which is not fixed in labor contracts and linked to economic conditions and firm performance (see Gimpelson and Kapelyushnikov 2011). Another is the low minimum wage level.[1] This suggests that firms may easily adjust wages for local amenities and disamenities.

In this chapter, we provide new evidence on compensating differentials in the Russian labor market. We apply the theory of compensating differences to wage differentials across Russian regions. Our methodology is based on the econometric estimation of a Mincer-type wage equation augmented with regional characteristics (RC). Controlling differences in worker and job characteristics, we examine whether the correlations of individual wages with regional amenities and disamenities are consistent with predictions of the theory.

Our work has several important differences from the study of Berger et al. (2008). Firstly, we used the NOBUS database instead of the RLMS database; this allowed us to control for differences in regional employment composition much better (to achieve true "similarity" of workers). Moreover, our research does not suffer from the sample-size problem, when samples for local labor markets are comprised of only a few dozen observations. Secondly, in our theoretical and empirical analysis we explicitly consider migration costs (MC) and living costs. The failure to take these costs into account leads to biased estimates for compensations. Thirdly, most studies devoted to the topic including those on the US labor market neglect the problem of endogenous city or RC, which may also lead to biased estimates. Using unique Russian circumstances, we propose instruments which help us to overcome this problem. Fourthly, in addition to examining wage compensations for regional amenities and disamenities, we also analyze differentials in regional wages adjusted for significant regional factors. We show that after adjusting for regional amenities and disamenities, regional wages become positively correlated with interregional migration flows. This corresponds well to the results of studies on interregional migration in Russia.[2] Finally, we apply the theory of compensative differences to a later period of transition, when the Russian economy and labor market have had more time to adjust to market forces.

Besides providing new empirical evidence on compensating differentials in the labor market of the largest transition economy, our study also contributes to the understanding of the phenomenon of interregional wage differentiation in Russia. Even in such large countries as the USA, Canada, or China, the magnitude of territorial wage differences is much lower than in Russia. A striking example is that even if one divides the territory of the USA into 363 metropolitan statistical areas (MSA), the variation in wages across them is lower than the variation across

[1] Although since 2007 the minimum wage level in Russia substantially increased, the Kaitz index (which is the ratio of minimum wage to the average wage) is still low compared with the OECD countries (Muravyev and Oshchepkov 2012) and most of the CEE countries.

[2] The internal migration in Russia, in spite of being low by international standards, can be explained by differences in living costs, regional amenities and disamenities, and opportunities on regional labor markets, see e.g., Andrienko and Guriev (2004) and Gerber (2006).

Russian regions.[3] As wages constitute the principal part of household incomes, high interregional wage differentials inevitably cause income disparities between citizens from different regions and social tensions. Moreover, these differentials have a significant impact on the overall wage inequality in the country.[4] Potentially, high cross-regional wage variation may provide an explanation for the fact that the level of wage inequality in Russia is higher than in other transition countries (e.g., Mitra and Yemtsov 2006; Lukiyanova 2011). However, the literature concerning interregional wage differentials in Russia is rather limited, and an explanation for this phenomenon is still lacking.

In our study, we estimate the extent to which the observed wage differentiation across regions may be considered as compensative. We show that wage compensations along with differences in employment composition are able to account for about three-fourths of the observed variation in nominal wages across Russia regions. At that, cross-regional differences in amenities and disamenities including living costs explain more variation than differences in employment composition.[5] These finding suggests that only a small part of the existing cross-regional variation in nominal wage translates to differences in real well-being.

This chapter, naturally, intersects with a large body of literature studying the association between regional wages and unemployment. There are two well-known opposite views. On one hand, the theory of compensating differences suggests a positive relation between regional wages and unemployment (Hall et al. 1972; Reza 1978; Marston 1985; Topel 1986). On the other hand, the wage curve literature suggests a negative relation between them (Blanchflower and Oswald 1994). The latter was found in most CEE countries (e.g., Iara and Traistaru 2004). In Russia, Blanchflower (2001) first found negative correlation between unemployment rates and average nominal wages across 14 regions in 1995–1997. Shilov and Moeller (2009) examining a longer period, 1997–2006, and including in the analysis all Russian regions confirmed this negative correlation. However, in our study we find a positive correlation between regional unemployment rates and individual wages in Russia which contradicts these findings. We receive a negative correlation *only if* we do not include regional price indexes and other nonpecuniary RC in our wage equations. Therefore, our results question empirical evidence on the wage curve, at least in the Russian case, and favor the compensating differences framework.

[3]As the magnitude of differentiation depends on the country's particular administrative division, we used several variants of divisions. All results are presented in Table 4.1.

[4]Standard decompositions of the total wage inequality show that the effect of the regional factor on the wage inequality is the largest in comparison with other factors such as human capital characteristics, industries and occupations (e.g., Lukiyanova 2008; Oshchepkov 2009). At the same time, the impact of the regional factor on the total wage inequality in Russia is much higher than that in OECD countries (see Oshchepkov 2007).

[5]This result contrasts to conclusions of Combes et al. (2008) for France that spatial wage differences in France are mainly explained by differences in employment composition. However, this may be easily explained by much greater spatial variation in amenities and disamenities in Russia than in France.

Our study is also closely linked to the issue of cross-regional unemployment disparities, which received much attention in transition countries due to their persistence. Many scholars view these disparities through the lens of massive structural change in the start of transition (for a recent review of papers see Ferragina and Pastore 2008; Pastore 2012). CEE and CIS countries experienced liberalization and changes with different speed and intensity, and even within countries reallocation process was very uneven favoring economic development in one region and heightening problems in others. High and relatively persistent unemployment disparities exist in Russia as well (e.g., Kapelushnikov and Vishnevskaya 2003; Bornhorst and Commander 2006), and it might be expected that, in general, their emergence and subsequent dynamics should conform to regularities documented in the CEE countries.[6] However, one of our conclusions that the rate of unemployment can be considered as a component of the cross-regional compensating mechanism advocates the relevance of the traditional neoclassical view on persistent spatial unemployment disparities, although after more than 10 years of economic and institutional transformations and only in the specific Russian case.

The chapter is organized as follows. The second section discusses the principal assumptions, predictions, and problems of applying the theory of compensative differences. The methodology and data used in our study are described in the third section. Empirical findings are discussed in the fourth section. The conclusion and directions for future research will be given in the last section.

4.2 Compensating Wage Differentials Between Regional Labor Markets: A Theoretical Background

The foundations of the modern theoretical and empirical framework of analyses of compensating wage differentials between cities or regions of a country were developed by the studies of Rosen (1974) and Roback (1982). Roback (1982) in her seminal paper formulated the general prediction of the neoclassical theory with respect to interregional wage differentials as follows: workers with similar characteristics should attain the same level of utility across regions. Utility functions of employees include not only wages but also living costs and various regional amenities and disamenities. Workers will prefer staying in a region with worse living conditions, if the corresponding loss in the level of utility is compensated by higher wages. More recent theoretical work and empirical research on migration decisions

[6]At the background of rich literature on the CEE countries, papers focusing on Russia are rare. The only study known to us is that of Bornhorst and Commander (2006). They examined regional unemployment in five transition countries: Chezh Republic, Hungary, Poland, Romania, and Russia. Most of the results show that correlations between regional wages, unemployment rates, and migration flows in Russia clearly differ from those in the other four countries (see, e.g., Figs. 3 and 4 in Bornhorst and Commander 2006).

clearly supported this framework (e.g., Knapp and Graves 1989; Greenwood et al. 1991a, b).

The reasonable assumption originating from the famous work of Harris and Todaro (1970) is that employees compare expected, rather than relative, wages. The regional unemployment rate presents a natural measure for the probability of not having a job in a region. In interregional equilibrium, when workers do not have any reason to migrate, expected wages should be equal across regions. This theory suggests a positive relation between regional wages and unemployment that was confirmed by empirical studies (Marston 1985).[7]

The compensative nature of interregional wage differentials should be viewed not only from the labor supply perspective but also from that of labor demand. Firms should be able to pay compensations for worse living conditions. While in the public sector, the remuneration of workers may automatically include regional supplements, in the private sector, higher wages mean higher costs and under the conditions of perfect competition directly lead to exclusion from the market. This implies that either the assumption of perfect competition does not hold, or certain regions have characteristics that allow firms to lower production costs. In the former case, various deviations from the perfect competition conditions, including monopsony at the labor market (e.g., Manning 2003), imperfect competition at the market of goods and rent sharing (e.g., Blanchflower et al. 1996; Nickell 1999), and agglomeration economies (Fujita and Tisse 2002), may allow firms to pay higher wages and, thus, attract workers. These violations may be also viewed as elements of the labor demand side of the "story" of interregional wage differentials.[8] In the latter case, there are so-called productive regional amenities which were initially modeled by Roback (1982) and more explicitly presented in the paper by Beeson and Eberts (1989).[9]

However, the theory of compensative differences may face a number of difficulties in its empirical implementation. The fundamental issue is the influence of shocks accompanied with positive MC.

The fact is that at any given moment, the interregional wage structure may reflect not only regional endowments in amenities and disamenities but also the influence of regional shocks. Shocks may arise on the side of labor demand, e.g., by a rise in the price for goods of regional specialization. Such a positive shock would lead to a growth in labor demand and push up the regional equilibrium wage. Shocks may arise on the side of labor supply, such as the demographic shock that arises when a relatively large demographic cohort enters the regional labor market. Such negative shocks lead to a growth in the regional labor supply and a reduction in wages.

[7]The wage curve assumes the opposite relation between individual wages and unemployment.

[8]Possible deviations from the perfect competition conditions in the Russian context are discussed in Oshchepkov (2009).

[9]The concentration of highly productive employees may also explain why firms operate in regions with a relatively high wage level. In this chapter, we control for the regional employment composition, and therefore this possibility is accounted for.

The effects of shocks complicate the testing of the theory of compensating differences. If the adjustment to shocks is prolonged and regional wages are subjected to shocks, then monetary evaluations of regional disamenities (compensations in terms of wages) are biased. For example, if an observed wage level in regions with more favorable living conditions is lower (higher) than the equilibrium wage level, then the monetary prices for nonpecuniary amenities will be overestimated (underestimated) in those regions (Greenwood et al. 1991a). It is noteworthy that a negative correlation between the level of regional attractiveness for residency and the regional wage level may not even exist, if the "splashes" of regional wages are not controlled for. This may be the case when, for instance, a positive shock occurs in a region with relatively favorable living conditions.

The analysis becomes more complicated because of the fact that different shocks exert a prolonged influence on the size and structure of interregional disparities. According to the estimations by Blanchard and Katz (1992), the effect of a shock on wage structure across American states disappears only in 7–10 years. Such a speed of adjustment is high compared to regions in the EU (Bentivogli and Pagano 1999). Therefore, regional wages may be under the influence of long-standing shocks and controlling for shocks only at the moment of analysis may not be sufficient. The important question arises: how should one account for biases in the estimates for compensations in the presence of regional shocks?

In order to answer this question, it is necessary to understand the reason why various shocks exert a prolonged influence on regional labor markets. This reason lies in the failure of the assumption of absolute labor mobility. Indeed, if there is absolute labor mobility, then an immediate inflow or outflow of workers results after a negative (positive) regional shock and the interregional wage structure is restored. However, an immediate movement between regions is not possible. One can list a variety of factors that hamper migration. First of all, there is incomplete information. Movement to a new place of residence requires information about the employment opportunities and the possibilities of renting or buying a home. Secondly, there is underdevelopment of the housing market. This includes a lack of acceptable options for accommodation, an underdeveloped mortgage system, and the relatively high transaction costs of the real estate market. Thirdly, there are liquidity constraints: in addition to housing costs, migration implies the costs of moving and a need to have funds to live before settling in. Fourthly, there are family, social, and cultural ties (see Mincer 1978). Fifthly, labor migration to other regions often leads to the depreciation of human and social capital, reducing the potential benefits from migration. Sixthly, there may be administrative barriers to migration.

All these factors generate positive MC. And it is the magnitude of these costs that determines how the interregional wage structure adjusts to regional shocks. If the movement costs are low, then workers are more mobile and the adjustment to shocks is faster and more complete. If the movement costs are high, workers are less mobile and the influence of a shock is more persistent. In the extreme case, when the costs are prohibitive and migration does not take place, the effects of regional shocks on regional wages are not mitigated at all.

These arguments bring us to the following: *because of the effects of various shocks and given positive MC, interregional wage differentials reflect not only regional endowments in amenities and disamenities but also the magnitude of MC.* This has several implications, which are very important for empirical analysis.

Firstly, if positive MC are not taken into account, as in the case when shocks are not included in an econometric model, the estimates for compensations in terms of wages for regional amenities and disamenities may be biased. The estimates may be under- or overestimated depending on what region (with more favorable or less favorable conditions, respectively) a "splash" in wages has occurred. Moving towards absolute labor mobility through the removal of barriers to migration and the reduction of MC may lead either to a rise or fall in interregional differentials in (nominal) wages. It should also be noted that a negative correlation between regional "favorableness" and regional wages might not be observed at all without controlling for MC.

Secondly, the factors hampering migration affect different groups of employees in different ways. Consequently, MC vary with certain worker characteristics. For instance, many theoretical and empirical studies indicate that employees with a higher level of human capital and younger employees have a higher propensity to migrate (see, for example Goldfarb and Yezer 1976; Topel 1986; Dickie and Gerking 1987).[10] If so, then more mobile workers, *ceteris paribus*, will receive larger wage compensations because they can choose a better combination of pecuniary and nonpecuniary RC (a bundle of goods comprising wages and amenities) than workers, who are less mobile. In addition, the wages of those workers who face higher MC are more affected by regional shocks (Topel 1986).

Thirdly, the level of MC differs across regions. The costs of both migration in a region and migration out of a region increase because of the underdevelopment of the regional housing market, the remoteness of the region, or the presence of administrative barriers. A high level of MC in a region implies a weak adjustment of wages in this region to shocks originating both from this region and from other regions. Therefore, a wage level in regions with high MC will not be similar to the wage levels in regions with similar living conditions but low MC.

4.3 Methodology and Data

The methodology is based on the estimation of the wage equation augmented with RC:

$$\mathrm{Ln}\left(W_{ij}\right) = A + B \times X_{ij} + C \times \mathrm{RC}_j + D \times S_j + E \times \mathrm{MC}_j + e_{ij} \tag{4.1}$$

[10] A possible explanation for this fact is that such employees face a smaller depreciation of accumulated human capital. At the same time, younger employees are on average less constrained by family and social ties.

where $W_{i,j}$ is the wage of worker *i* from region *j*; *X* is the set of worker and job characteristics that reflect the regional employment composition; RC is the set of regional characteristics (amenities, disamenities, and living costs), for which workers demand compensation in terms of wages; *S* is the set of variables that controls for the influence of shocks on the interregional wage structure; MC are the variables that control for the presence of positive migration costs; *A* is the global constant; *B*, *C*, *D*, and *E* are the matrices of coefficients that are to be estimated; e is an error term, reflecting the influence of unobservable factors on individual wages.

It is expected that the set of coefficients (C) will be significant. In other words, it is expected that RC will influence individual wages, if one considers similar workers (*X*), controls for the influence of regionally specific shocks (*S*), and accounts for positive MC.[11] The theory of compensating differences predicts that the coefficients for regional amenities will be negative, while the coefficients for disamenities and productive amenities will be positive.[12]

Adjustment of Interregional Wage Differentials In order to see how the adjustment for regional employment composition and RC influence the scale of interregional wage differentials, we follow the methodology introduced by Dumond et al. (1999). We estimate separately three equations: the first one contains only (*X*), the second one contains (*X*) and (RC), and the third one is the full specification (4.1), including controls for shocks (*S*) and MC. After the estimation of each of these specifications, we calculate two measures of interregional wage differentials: the weighted standard deviation (WSD) and the weighted mean standard deviation (WMAD).[13] The calculation of these measures is based on residuals: for every specification for each region, we calculate the mean residual, which reflects the deviation of the mean regional wage from the national average. It is expected that adjusting the interregional wage differentials for different regional employment compositions and different endowments in amenities and disamenities will considerably decrease the scale of interregional wage differentials (Table 4.1).[14]

Data A micro-database is needed for this study, one which would be representative both at the national and regional levels. Russian Labor Force Survey (LFS) does not contain information about wages, and the widely used Russian Longitudinal Monitoring Survey (RLMS) is not regionally representative. The only appropriate

[11]In estimating Eq. (4.1), one should take into account possible regional clusterization of errors which leads to the underestimation of standard errors of coefficients at the regional characteristics (e.g., Moulton 1990).

[12]Productive regional amenities are amenities that allow firms to decrease costs, see Roback (1982) and Beeson and Eberts (1989).

[13]A similar methodology was used earlier by Krueger and Summers (1988).

[14]It should be noted that it is impossible to adjust interregional wage differentials for regional characteristics with the use of regional dummy variables because of the problem of total multicollinearity. Papers that used regional dummies adjusted only for the regional employment structure (see, for example, Haisken-DeNew and Schwarze 1997; Azzoni and Servo 2002; Garcia and Molina 2002; Viera et al. 2005).

Table 4.1 Interregional wage differences in Russia and other countries

Country	Number of regional units	Comments	Period	Max/Min	Coefficient of variation
Germany	16	Federal lands	2003	1.56	0.147
France	26	Regions	2002	1.57	0.087
Australia	8	6 states + 2 territories	1996–2001	1.28	0.083
Canada	10	Provinces	2003–2007	1.32	0.081
Canada	13	10 Provinces + 3 territories	2003–2007	1.60	0.135
USA	51	50 states + Columbia District	2001–2002	2.22	0.184
USA	363	Metropolitan statistical area (MSA)	2001–2002	3.79	0.191
USA	49	49 states (without Wyoming)	2005–2007	1.81	0.130
China	22	Provinces (without Taiwan)	2005–2006	1.84	0.188
China	27	22 Provinces + 5 autonomous Regions	2005–2006	2.00	0.209
China	31	22 Provinces + 5 autonomous regions + 4 cities of central jurisdiction	2005–2006	2.55	0.305
Belarus	7	6 Regions + 1 city of central jurisdiction	I q 2005	1.47	0.152
Ukraine	27	24 Regions + 2 cities of central jurisdiction + 1 autonomous Region (Crimea)	2002–2004	2.71	0.255
Russia	**79**	**Subjects of Russian Federation**	**2003–2007**	**6.35**	**0.447**
Russia	**79**	**Subjects of Russian Federation**	**2009**	**4.66**	**0.391**

Comments: (1) Calculated by author using official aggregate data taken from national statistical offices (without adjustment on possible interregional prices differences); (2) The use of some other inequality measures including general entropy and Gini indexes gives the same qualitative results

database is the National Survey of Household Welfare and Participation in Social Programs, also known as NOBUS.

This household survey was developed with the technical assistance of the World Bank and conducted by Federal Service of State Statistics (Rosstat) in the spring of 2003. The advantages of this dataset are its large sample and its regional covering. The survey uses a random sample of about 45,000 households and more than 115,000 people. Such sample size allows obtaining representative data both at national and regional level for 47 out of 89 subjects of the Russian Federation, where approximately 72 % of the total population live.[15]

The monthly average wage on a worker's main job is used as a measure of individual wage. 98 % of all observations were collected in May 2003; therefore, we do not deflate wages. Observations from the lowest and highest 0.1 % of the wage distribution were treated as outliers and excluded from the sample. Only a minority of workers had wage arrears at the moment of survey, and these wage arrears were not concentrated in any group of workers based on industry or skill. Therefore, we do not adjust wages for nonpayment as was commonly done in studies on Russia in the 1990s. Descriptive statistics for the NOBUS sample are presented in Table 4.2. Characteristics listed there constitute the set (X) of worker and job characteristics. The inclusion of this set of individual characteristics in the equation allows us to control for interregional differences in the employment composition. According to NOBUS, nominal wages are highest in the cities of Moscow and Saint Petersburg and their surroundings and in the Northern and North-Eastern regions of the country. Among the outsiders are the regions of the Southern and Central Federal Districts.[16] This pattern corresponds well to what is observed on the official Rosstat data on aggregate regional wages.

In addition to micro-data, we use aggregated RC, which are published by Rosstat. We match these characteristics with the NOBUS database. As there is no theory that predicts which RC are compensated in terms of wages, the choice of RC is determined by the previous papers on Russia and other countries, and also, of course, by the availability of regional data. The list of selected characteristics contains living costs (regional price index), the expected lifetime, the average temperature in January, the crime rate, the air pollution level, medical staff per 10,000 citizens, the number of buses (per 100,000), the density of asphalt roads (km per 1,000 km^2), the number of telephones (per 1,000), and the regional unemployment level.[17] The descriptive statistics for all RC used in the study are presented in Table 4.3.

Two variables of the set (S) were constructed using official Rosstat data on GDP and Gross Regional Products (GRPs). The first variable is the deviation of the GRP growth rate in 2002 from the regional growth trend. The regional growth trend is presented as the average growth rate for the period 2000–2005. If this variable is more (less) than one, then a positive (negative) shock in the region has occurred. The second variable is the average deviation of GRP growth rates from the GDP growth rate for the period 1999–2003. This variable reflects interregional differences

[15]These data were used in a number of studies on Russia; see Gustafsson and Nivorozhkina (2011) and Staneva et al. (2010) among recent examples. More information on NOBUS is available on the site of World Bank (see http://go.worldbank.org/VWPUL3S9F0).

[16]For more details see Table 4.3 in Oshchepkov (2007).

[17]We do not need control for different tax and transfer systems in regions (as, e.g., Johnson 1983), because the personal income tax rate in Russia is equal to 13 % in all regions and social security payments are rather low comparing to wage levels.

Table 4.2 Description of the NOBUS sample

	%
Gender	
Male	47.4
Female	52.6
Education	
No primary and primary	0.9
Primary general	7.0
Secondary	20.3
Primary vocational (with complete secondary)	8.4
Primary vocational (without complete secondary)	3.9
Secondary vocational	34.3
Higher (not completed)	3.6
Higher and postgraduate education	21.7
Occupations	
Management	2.6
Leading specialists	14.4
Specialists	20.0
Clerks	5.7
Workers in facilities	14.2
Qualified workers in agriculture	4.1
Qualified workers	16.3
Operatives and other	6.7
Nonqualified workers	14.3
Military forces	1.8
Settlement	
1 million and more	10.8
500–999,9 thousands	9.1
250–499,9 thousands	14.4
100–249,9 thousands	11.1
50–99,9 thousands	7.3
20–49,9 thousands	9.5
5–20 thousands	14.0
Village	24.0
Industry	
Agriculture, hunting, forestry	8.6
Fishing	0.9
Extracting industry	2.7
Manufacturing	14.9
Energy, gas, and water supply	3.8
Construction	6.8
Trade	11.6
Hotels and restaurants	1.2
Transport, communications and storage facilities	9.5

(continued)

Table 4.2 (continued)

	%
Financial services	1.2
Realtors and other commercial services	1.2
Government + military forces	9.0
Education	11.7
Health and social programs	8.6
Municipal and social services	7.7
Others	0.8
Tenure	
Less than 1 year	13.4
1–3 years	19.5
3–5 years	12.7
5–10 years	17.0
More than 10 years	37.5
Mean age (years)	39.9
Wage (roubles, after taxation)	3,502.3
Working hours (weekly)	41.0
N	46,680

in the speed of adjustment to the 1998 macro-shock. Additionally, we construct a variable reflecting the proximity of a region to the military conflict in the republic of Chechnya. This variable is a dummy and equals one if a region borders Chechnya.[18]

Government Regional Wage Coefficients When examining correlations between RC and individual wages in Russia, one has to control for the existing government system of regional wage coefficients. It was designed yet in the Soviet period to compensate worse living conditions in the Northern territories. Therefore, the detected correlations may be potentially not a result of the market compensative mechanism, but rather a result of the government one. At present, these regional wage coefficients exist in 21 Russian regions. Their magnitude varies from 1.15 (most of the Republic of Karelia) to 2 (e.g., Chukotka) with several regions having small districts in which wage coefficients differ.[19] In such cases, we constructed wage coefficients for a whole region as a weighted average of district coefficients,

[18]Only three regions, the Republics of Dagestan and Ingushetiya and the Stavropol Region, border Chechnya.

[19]Peculiarities of the system of labor compensation in the Northern territories are described in the article No. 50 of the Russian Labor Code. The magnitude of regional coefficients and the order of their implementation are set by the Russian government. A current list of areas and the magnitude of corresponding wage coefficients are presented in the joint information letter by the Pension Department of the Ministry of Labor (dated by 09.06.2003, No. 1199–1116), the Department of Incomes and Welfare of Population of the Ministry of Labor (dated by 19.05.2003, No. 670–679), and Russian Pension Fund (dated by 09.06.2003, No. 25–23/5995).

Table 4.3 Regional characteristics used in analysis (2003)

	Mean	Median	Minimum	Maximum	Country mean
Characteristics of the set (RC)					
Regional price index (rubles)	3,570.6	3,291.4	2,877.7	7,962.3	3,577
			Tambov Region	Chukotka autonomous Region	
Life expectancy (years)	64.3	64.0	54.3	75.1	65.07
			Republic of Tyva	Republic of Ingushetia	
Average temperature in January (°C)	−11.39	−10.7	−34.9	2.6	−11.39
			Republic of Sakha (Yakutia)	Krasnodar Region	
Crime rate (per 100,000 citizens)	1,901.0	1,897.0	326	3,232	1,907
			Republic of Ingushetia	Jewish autonomous Region	
Air pollution (tons per 1 km^2)	3.63	1.1	0.04	88.18	1.16
			Republic of Sakha (Yakutia)	Moscow	
Medical staff (per 10,000 citizens)	165.6	163.6	64.2	316.3	159.6
			Republic of Ingushetia	Chukotka autonomous Region	
Buses (per 100,000 citizens)	62.6	64.0	10	119	64
			Sakhalin Region	Magadan Region	
Road density (km per 1,000 km^2)	116.45	119	0.8	352	32
			Chukotka autonomous Region	Moscow Region	
Stationary telephones (per 1,000 citizens)	225.6	230.6	47	348.2	240
			Republic of Ingushetia	Saint Petersburg	
Regional unemployment level (%)	10	9.1	1.3	53.1	8.6
			Moscow	Republic of Ingushetia	
Characteristics of the set (S)					
Deviation of the GRP growth rate in 2002 from the regional growth trend (Shock-1)	0.95	0.95	0.56	1.12	0.92
			Republic of Ingushetia	Primorsk Region	

Average deviation of GRP growth rates from the GDP growth rate (Shock-2)	0.96	0.96	0.82	1.08	1
			Republic of Kalmykia	Jewish Autonomous Region	
Characteristics of the set (MC)					
Distance from the regional capital to Moscow (km)	1,790.60	1,087.70	0	6,784.92	–
			Moscow	Kamchatka Region	

weighting by share of regional population living in districts where coefficients are set.

In implementing our methodology, we have to take into account several difficulties. This is endogeneity of RC, instability of coefficients of RC, unobservable costs of interregional migration, and heterogeneity of workers.

Endogeneity of Regional Characteristics There are two kinds of RC that may be endogenous in the econometric framework described above. These are living costs and regional infrastructure. A source for their endogeneity is omitting a level of regional economic development.

Concerning living costs, one can expect that in rich regions the demand curve is located higher than in poorer regions; therefore, a higher wage level implies a higher price level. The fact that it is correct only for non-tradable goods does not weaken the problem. In many papers, in order to account for the differences in living costs across territories, either housing prices were used, or they were included in the price index and determined most of its interregional variation (see, for instance, Johnson 1983; Roback 1988; Furdato 1996; Dumond et al. 1999). But housing clearly is a non-tradable good; its price is endogenous with respect to the regional wage level. This casts doubt on the unbiasedness and consistency of the coefficient of the regional price index, if it contains housing prices.

Exclusion of living costs from regressions naturally helps to avoid the problem of endogeneity of living costs. Regional differences in living conditions may potentially account for a significant part of the interregional variation in living costs, including housing (or land) prices. Some papers show that including living costs into the wage equation together with nonpecuniary RC increases the interregional variation in wages (e.g., Roback 1988). This can be viewed as an argument to not include living costs in the wage equation. However, such a practice seems to be dubious. The regional price levels are themselves a very important factor of migration decision, and the theory predicts that it is not wages but their purchasing power what matters. Moreover, in practice it is not possible by definition to take into account all RC that determine variation of price levels across regions. So, by excluding living costs one omits an important factor from a model.

The price index in Russia does not include housing prices. It is calculated by the Rosstat and officially recommended for interregional comparisons. It sums prices for a fixed set (which is the same for all regions) of goods and services. The underlying set contains such goods as gasoline, clothing, and food. Most of these goods are tradable. Interregional variation in prices for these goods is caused by transportation costs and does not depend on regional incomes in the long run.[20] The share of services in the price index is less than 30 % and services, prices for

[20]A higher wage level in a region may push up regional prices in the short run. However, in our theoretical framework, we consider the long-run period, when an interregional wage structure is close to the state of equilibrium. In the long run, relatively high prices in a region will attract producers (sellers) to the market. They will increase their supply of goods up until the benefit (that is the difference between prices in two regions) is less than transportation costs. Therefore,

which do not directly depend on incomes of regional population, constitute about three quarters of this amount.[21] Given the structure of regional price indices, we can derive a conclusion that unlike many other international studies, the Russian regional price index may be treated as exogenous with respect to regional incomes and wages.[22, 23]

It should be noted that along with the option of including or not including measures of living costs in the equation, one can use a full adjustment of wages for living costs, i.e., divide individual wages by the corresponding regional price level before estimating the augmented wage equation. Dumond et al. (1999) argue that inclusion of the regional price levels in the left-hand side of the wage equation is a preferable way of considering regional living costs. The full adjustment implicitly assumes that the elasticity of the equilibrium wage level with respect to the local prices is equal to one. But there is no theory that predicts why it should be equal to unity; it is one of the research questions to estimate this elasticity.

Omitting the level of regional economic development also presents a source of potential endogeneity of characteristics of regional infrastructure. One can expect that in rich and developed regions, the wage level is higher and the regional infrastructure is better than in poorer regions. It implies that coefficients of regional amenities (disamenities) may be biased downward (upward). It is difficult to avoid this problem, because, on the one hand, the characteristics of the infrastructure must be included in the equation, but, on the other hand, it is hard to find any auxiliary (instrumental) variables that reflect interregional differences in infrastructure and, at the same time, are not correlated with the level of regional development. This difficulty might explain why this question did not receive any attention in the literature on compensative interregional wage differentials.

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an interregional structure of prices for tradable goods in long run is determined by transportation costs and does not depend on regional wages.

[21]These services are public conveyances, communication, and public utilities. For more information about the composition of the price index see in “Ceni v Rossii” (“Prices in Russia”), Rosstat (2004).

[22]We should note that the price index for a common set of goods and services is a Laysperes price index. However, the optimal consumption structure may differ across regions, and so differences in regional price levels may either overestimate or underestimate the differences in the levels of utility that were brought about by these price differentials. In our study we do not control for this possibility.

[23]In earlier versions of our paper we included regional housing prices to the regressions along with the price index. There are two reasons why we excluded housing prices from this version. Firstly, housing is a very specific good comparing with other goods and services included in the fixed set. The prices for housing are much higher than for “standard” goods, and people purchase houses much more rarely than such good as, for example, food and clothes. Although people may also rent housing, these expenditures are also higher than expenditures on “standard” goods and services, and only about 2.7 % individuals from the regression sample rented housing. Secondly, unfortunately we did not manage to find an appropriate instrument for housing prices, which would be correlated with them, but not correlated with regional incomes.

In this study, we assume that unique Russian conditions allow us to solve the problem of endogeneity of characteristics of regional infrastructure. Under a planned economy, the level of development of the regional infrastructure in Russia was determined centrally and exogenously with respect to regional economic development. Taking into account the high correlation between the indicators of regional infrastructure development in 1990 and 2003, one can use the indicators of 1990 as convenient instruments for the indicators of 2003. In this study, we instrument four regional indicators—medical staff per 10,000 of population, the number of buses (per 100,000), the density of asphalt roads, the number of telephones per 1,000 citizens—by using their 1990 values.[24]

Instability of the Estimates of the Regional Coefficients The asymptotic properties of the coefficients of RC are determined not by the number of individual observations, but by the number of observations on the regional level, which is equal to 79 in our sample. Under such circumstances, the problem of the multicollinearity of RC becomes more acute. It implies that the significance of the RC coefficients is very sensitive to the specification of Eq. (4.1), and this may significantly affect the interpretation of the estimated coefficients. In this study, we take this problem into account and interpret only those dependencies that are robust in all specifications.

Migration Costs As mentioned above in Sect. 4.3, there is a long list of factors that may hamper interregional labor mobility. Unfortunately, many of these factors are difficult to formalize in order to use them in an empirical analysis. Moreover, the size of MC depends on the characteristics of both origin and destination regions, but micro-data for this does not exist in Russia. In addition, currently, there are no studies that offer estimates for the costs of migration between Russian regions.

In this study, we use the geographical distance from the capitals of the regions to Moscow as a proxy variable for the level of positive MC. Here, we implicitly assume that for migrants from every region, Moscow is the region of destination. Such an assumption is not far from reality, because Moscow (along with the Moscow region) is the principal region that attracts migrants in Russia.[25] It is also assumed that differences in geographical distance reflect differences in transportation costs, thereby accounting for MC induced by such factors as the need to pay to move. It

[24]A similar method to solve the problem of endogeneity in the wage regression framework was used by Moretti (2004). He instrumented the percentage of college educated workers in the labor force of a city by the presence of land-grant colleges (which were founded in 1862 in the context of the federal program). For Russia, a similar method was used in Muravyev (2008). The author argued that the educational structure of cities under the central planning was determined by the federal government rather than by the market and instrumented the 1994 share of people with higher education with the respective share in 1989.

[25]According to Rosstat, during the period from 2000 to 2005, the net migration coefficient was the highest in Moscow and the Moscow region (if data on the Republic of Ingushetia are not considered). In 2002, Moscow and the Moscow region had a positive exchange of migrants with 47 regions; the Tumenskaya Region had the next largest positive migration balance, with seven regions.

should be clear that accounting for MC in this way fails to take into consideration the costs of migration induced by many other factors.

Heterogeneity of Workers The method used in this study assumes that including the set of worker and job characteristics (*X*) in the wage equation allows us to consider interregional wage differentials across similar workers. However, the heterogeneity of workers can influence estimates not only through different worker (and job) characteristics. Firstly, different types of workers may have different preferences with respect to RC. Secondly, workers may have different propensities to migrate. In both cases, the level of compensation for the same RC will not be equal across workers.

Therefore, we estimate Eq. (4.1) both for the total sample of workers and also for several subsamples. Firstly, we distinguish young workers with and without children in a household. According to the Rosstat, both men and women aged 15–29 are much more mobile than other age groups.[26] The presence of children in the household, in turn, considerably reduces mobility. We assume that young people with children will be less mobile than young people without children. Second, we distinguish between workers with the secondary education and workers with the higher level of education. We assume that the latter are more mobile than the former. It might be expected that more mobile groups of workers will receive on average a higher level of wage compensation, because they are able to choose from a wider set of "wage–amenity" pairs. However, it should be noted that the preferences of workers might differ.

4.4 Results and Discussion

The estimation results of the wage equation generally support the findings of other papers on Russia using both NOBUS and RLMS data at the period after 1998 crisis.[27] Firstly, wages grow with the level of education. For instance, individuals with higher education receive about 30 % more than individuals with primary education. Secondly, wages are positively correlated with age but negatively with age squared. Thirdly, there are significant wage premiums in the extracting industry, energy, transport, and communications. Employees in the public sector (education and health) and agriculture receive lower wages. Fourthly, there is a clear wage hierarchy in occupations. Finally, the size of the settlement, ceteris paribus, positively affects individual wages.[28]

[26]Rosstat, "Demographic yearbook", 2001–2007 issues.

[27]See, for example, Gimpelson and Lukiyanova (2009).

[28]This may be due to different agglomeration effects: input–output linkages, thicker markets with better employer–employee matching and higher specialization of workers, knowledge accumulation, or the localization of HC externalities, etc. (Fujita and Tisse 2002).

However, the main interest of our study lies in the analysis of the influence of RC on individual wages. The estimation results are shown in Table 4.4. The six columns of the Table present results for six specifications of the wage equation. Specification 1 includes all RC and was estimated by simple OLS. Specification 2 was estimated taking into account the clusterization of errors within regions.[29] This increases standard errors of the coefficients for RC, and some of them even become insignificant.

In Specification 3, the four infrastructure variables were instrumented by their 1990 values (as discussed in *the Methodology section*).[30] The significance of all instrumented variables decreases, and two of them (medical staff per person and availability of buses in a region) become insignificant even at the 10 % significance level. This finding may indicate that the significance of these RC in Specification 2 is explained by the "welfare effect," i.e., by their endogeneity with respect to the regional wage level. At the same time, we should not forget that the significance of the coefficients of RC may be affected by their multicollinearity.[31]

Specification 3 also shows that variables controlling regional shocks do not influence individual wages. Specification 4 confirms that excluding the two shock variables from the equation does not alter the estimated coefficients of the RC. We conclude that the estimates of coefficients of the RC are not biased with respect to regional shocks, and therefore the shock variables are excluded from further analysis.

It is noteworthy to discuss the effects of the inclusion of distance from a region to Moscow (a variable reflecting MC) in the equation. A comparison of columns 4 (containing the distance) and 6 (without this variable) shows that accounting for positive MC changes the estimates of the coefficients of the RC. Although changes in most of the coefficients are not statistically significant, controlling for MC permits us to detect a positive and significant partial correlation between a regional unemployment level and individual wages. Positive correlation fully corresponds to the predictions of the theory of compensating differences. The unemployment level is a regional disamenity. It reflects the possibility of not having a job in a region, and, hence, should be compensated by a higher regional wage level. Such a finding is

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[29]The intra-class correlation coefficient estimated for residuals received from Specification 1 is positive and significant. This indicates that standard errors of coefficients for regional characteristics in Specification 1 are underestimated.

[30]Following recommendations presented in the Chap. 8 of Baum (2006), we employed a series of tests for the relevance of the instruments and the Durbin–Wu–Hausman test of the endogeneity of our infrastructure variables. We note that, unfortunately, these tests are not technically executable in the survey regression framework; therefore, we employed them estimating Specification 3 by simple OLS. The results of the tests are presented in Tables 4.5 and 4.6. The tests fully support the relevance of our instruments and the endogeneity of the infrastructure variables.

[31]We cannot exclude also the possibility that with the use of some other (unknown to us) instruments, the infrastructure variables in our regression will be significant. However, one can expect that the coefficient of a variable reflecting medical services will remain negative, because it is biased upward due to the "welfare effect."

Table 4.4 Influence of regional characteristics on individual wages

	Specifications					
	1 (OLS)	2 (OLS)	3 (2SLS)	4 (2SLS)	5 (2SLS)	6 (2SLS)
Price index (ln)	1.026** (0.031)	1.026** (0.094)	0.950** (0.118)	0.945** (0.126)	0.957** (0.124)	0.950** (0.130)
Life expectancy (ln)	−2.315** (0.165)	−2.315** (0.573)	−2.758** (0.646)	−2.732** (0.603)	−2.786** (0.639)	−2.749** (0.609)
Average temperature in January (°C)	−0.016** (0.001)	−0.016** (0.003)	−0,020** (0.004)	−0.020** (0.005)	−0.020** (0.004)	−0.021** (0.005)
Crime rate (per 1,000 citizens)	−0.010** (0.001)	−0.010** (0.004)	−0.010* (0.004)	−0.011* (0.004)	−0.010* (0.004)	−0.011* (0.004)
Air pollution (1,000 tons per 1 km^2)	0.105** (0.006)	0.105** (0.019)	0.141** (0.027)	0.131** (0.026)	0.144** (0.026)	0.134** (0.026)
Medical staff (per 10,000 citizens)[a]	−0.003** (0.000)	−0.003** (0.001)	−0.003 (0.002)	−0.003 (0.002)	−0.003 (0.002)	−0.004 (0.002)
Buses (per 100,000 citizens)[a]	0.002** (0.000)	0.002** (0.001)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)	−0.001 (0.002)
Road density (km per 1 km^2)[a]	0.053 (0.130)	0.095 (0.447)	0.894 (0.611)	0.783 (0.576)	1.039* (0.467)	0.946* (0.458)
Stationary telephones (per 1,000 citizens)[a]	0.002** (0.000)	0.002** (0.001)	0.003* (0.002)	0.003* (0.002)	0.003* (0.001)	0.003* (0.001)
Regional unemployment level (ln)	0.132** (0.016)	0.132** (0.051)	0.142* (0.064)	0.138* (0.068)	0.128 (0.075)	0.121 (0.079)
Proximity to conflicts (dummy)[b]	0.234** (0.037)	0.234 (0.131)	0.419 (0.242)	0.371 (0.234)	0.434* (0.215)	0.381 (0.221)
Control for migration costs (ln of distance to Moscow)	−0.031** (0.005) Yes	−0.031 (0.020) Yes	−0.009 (0.023) Yes	−0.011 (0.023) Yes	No	No

(continued)

Table 4.4 (continued)

	Specifications					
	1 (OLS)	2 (OLS)	3 (2SLS)	4 (2SLS)	5 (2SLS)	6 (2SLS)
Shock-1	0.236** (0.050)	0.236(0.234)	0.168(0.252)		0.157(0.252)	
Shock-2	0.378** (0.130)	0.378(0.428)	−0.319(0.552)		−0.391(0.536)	
Constant	6.070** (0.700)	6.070** (2.468)	8.798** (3.108)	8.712** (2.778)	8.897** (3.066)	8.695** (2.801)
R^2	0.517	0.517	0.514	0,514	0.514	0.514
No. of observations	46,340	46,340	46,340	46,340	46,340	46,340

Comments: (1) The construction of Shock-1 and Shock-2 variables that control for regional shocks is described in Data section. (2) Standard errors robust to heteroscedasticity and clustering are in parentheses
*Coefficient is significant at the 5 % level
**Coefficient is significant at the 1 % level
[a]These variables were instrumented by their own values for 1990
[b]This variable equals 1 for the Republics of Dagestan and Ingushetia and for the Stavropol Region, its value for the other regions are 0

Table 4.5 Tests for the relevance of the instruments

Instruments	Partial R^2*	F-stat.F(4,46276)	*P*-value of the F-stat.	Shea partial R^2**
Medical staff, 1990	0.3396	5,948	0.000	0.2633
Buses, 1990	0.4233	8,491	0.000	0.3311
Road density, 1990	0.8025	470,017	0.000	0.4415
Stationary telephones, 1990	0.3404	5,971	0.000	0.1786
Underidentification tests		*Test statistics*	*P-value*	
Anderson canon. corr. likelihood ratio stat.		Chi-sq(1) = 8,778.49	0.0000	
Cragg–Donald statistics[N × minEval]		Chi-sq(1) = 9,665.06	0.0000	
Cragg–Donald weak identification statistics[(N − L) × minEval/L2]		F-stat = 2,412.93		
Anderson–Rubin test of joint significance of endogenous regressors		F(4.46276) = 24.67 Chi-sq(4) = 98.83	0.0000 0.0000	

Comments: *Partial R^2 shows growth in the share of explained variation due to adding an instrument after all other instruments have been taken into account in the regression where the instrumented (endogeneous) variable is on the left-hand side, and all instruments are on the right hand side. The F-test (H0: an instrument should not be included in the regression, i.e., an instrument in irrelevant) is used to justify whether this growth in explained variation is statistically significant. **The Shea partial R^2 is the same as partial R^2 but it additionally takes into account possible correlations between instruments. For more details to all tests, see Baum (2006, Chap. 8)

Table 4.6 Tests for endogeneity of the infrastructure variables

Test	Test statistics	*P*-value
Wu-Hausman F-test	F(4,46272) = 33.98455	0.000
Durbin-Wu-Hausman chi-sq test	Chi-sq(4) = 135.73920	0.000

also consistent with the results from literature on interregional migration in Russia. Migration reacts to interregional differences in unemployment rates: people move from regions with higher levels of unemployment to regions with lower levels, other things being equal.[32] Therefore, they will stay in a region with a higher level of unemployment, if they receive a compensation for that.

It should be also noted that a regional unemployment level may be endogenous with respect to individual wages. A source of endogeneity here is an omitted regional factor reflecting regional economic development (see the corresponding discussion in section *Methodology and Data*). One can expect that in economically developed regions, the wage level is higher and the unemployment level is lower than in less developed regions. This predicts that the coefficient for the unemployment level is biased downward. Hence, we argue that a received estimate of the coefficient of the regional unemployment level is positive and significant in spite of a possible endogeneity bias.

Specification 4 could be chosen as the basis for interpreting the coefficients. The regional clusterization, "welfare effect," and positive MC were considered in this specification. Moreover, all RC are jointly significant at the 1 % level of significance. However, the problem of the instability of the regional coefficients has still not been considered. This problem, as discussed above in the methodology section, is caused by both technical and theoretical reasons. On one hand, some RC are correlated (see Table 4.7). On the other hand, RC considered by workers in their utility functions may substitute each other. For instance, a worker may prefer to live in a region with a higher crime level, but with a lower level of air pollution. These factors, given the small number of degrees of freedom (equal to the number of regions), result in a high sensitivity of the estimates of the regional coefficients to the specification form. Further analysis confirms that the exclusion of some regional variables alters not only the magnitude but also the significance of the estimates for the remaining variables.

The process of selecting a stable specification is presented in Table 4.8. Specification 4 was chosen as the starting point. First, we excluded the most insignificant regional characteristic (availability of buses) from the equation. This leads to changes in the size of the coefficients of some RC; however, these changes are not statistically significant (see Specification 7). Next, following the same principle of excluding the most insignificant regional variable, we successively exclude the density of roads (see Specification 8) and the dummy variable that

[32] See Andrienko and Guriev (2004) and Gerber (2006).

Table 4.7 Correlations of regional characteristics

	1	2	3	4	5	6	7	8	9	10	11	12
(1) Price index (ln)	1	−0.32*	−0.53*	0.30*	0.16	0.53*	−0.07	−0.43*	0.39*	−0.23*	0.25*	0.80*
(2) Life expectancy (ln)		1	0.64*	−0.66*	0.12	−0.15	0.29*	0.49*	0.13	0.14	−0.27*	−0.37*
(3) Average temperature in January			1	−0.58*	−0.05	−0.21*	0.16	0.69*	0.08	0.08	−0.42*	−0.50*
(4) Crime rate				1	0.15	0.19*	−0.19*	−0.55*	−0.12	−0.15	0.30*	0.16
(5) Air pollution					1	0.00	0.30*	−0.19*	−0.12	−0.14	0.02	0.11
(6) Medical staff						1	0.06	−0.13	0.59*	−0.35*	−0.05	0.50*
(7) Buses							1	0.09	0.01	−0.05	−0.01	0.15
(8) Road density								1	0.20*	−0.23*	−0.65*	−0.50*
(9) Stationary telephones									1	−0.40*	−0.33*	0.24*
(10) Regional unemployment level (ln)										1	0.55*	0.04
(11) Distance from the regional capital to Moscow											1	0.37*
(12) Regional wage coefficient												1

Comment: *Coefficient is significant at the 5 % level

Table 4.8 Excluding insignificant regional variables and introducing regional wage coefficients

	Specifications					
	4 (2SLS)	7 (2SLS)	8 (2SLS)	9 (2SLS)	10 (2SLS)	11 (2SLS)
Price index (ln)	0.945** (0.126)	0.964** (0.105)	0.910** (0.113)	0.966** (0.102)	0.981** (0.102)	0.847** (0.179)
Life expectancy (ln)	−2.732** (0.603)	−2.776** (0.627)	−2.416** (0.582)	−2.075** (0.532)	−1.803** (0.541)	−1.984** (0.524)
Average temperature in January (°C)	−0.020** (0.005)	−0.020** (0.004)	−0.018** (0.004)	−0.018** (0.004)	−0.018** (0.005)	−0.018** (0.004)
Crime rate (per 1,000 citizens)	−0.011* (0.004)	−0.098* (0.004)	−0.110** (0.004)	−0.118** (0.004)	−0.126** (0.004)	−0.106** (0.004)
Air pollution (1,000 tons per 1 km^2)	0.131** (0.026)	0.130** (0.024)	0.114**(0.017)	0.108** (0.017)	0.099** (0.016)	0.105** (0.016)
Medical staff (per 10,000 citizens)[a]	−0.003 (0.002)	−0.003 (0.002)	−0.004* (0.002)	−0.004* (0.002)	−0.005 (0.003)	−0.004* (0.002)
Buses (per 100,000 citizens)[a]	0.001 (0.002)					
Road density(km per 1 km^2)[a]	0.783 (0.576)	0.846 (0.627)				
Stationary telephones (per 1,000 citizens)[a]	0.003* (0.002)	0.003* (0.002)	0.003* (0.001)	0.003* (0.001)	0.003** (0.001)	0.003** (0.001)
Regional unemployment level (ln)	0.138* (0.068)	0.155* (0.085)	0.112 (0.060)	0.128* (0.063)	0.030 (0.065)	0.125* (0.065)
Proximity to conflicts (dummy)[b]	0.371 (0.234)	0.399 (0.257)	0.333 (0.226)			
Control for migration costs	Yes	Yes	Yes	Yes	No	Yes

Government regional wage coefficient						0.247 (0.337)
Constant	8.712** (2.778)	8.614** (2.616)	8.079** (2.582)	6.250** (2.433)	5.109* (2.560)	6.615* (2.586)
R^2	0.514	0.515	0.515	0.515	0.512	0.515
No. of observations	46,340	46,340	46,340	46,340	46,340	46,340

Comments: Standard errors robust to heteroscedasticity and clustering are in parentheses
Coefficient is significant at the 5 % level
*Coefficient is significant at the 1 % level
[a]These variables were instrumented by their own values for 1990
[b]This variable equals 1 for the Republics of Dagestan and Ingushetia and for the Stavropol Region, its value for the other regions is 0

reflects the proximity of a region to Chechnya (see Specification 9). Specification 9 contains only significant RC, and the further exclusion of variables does not alter the significance of the remaining variables. Comparison of the estimates in specifications 9 and 10 shows that inclusion of MC affects the estimates of RC; its effect on a regional unemployment level holds valid. Thus, we chose specification 9 as the final specification for interpreting the coefficients and the further calculation of adjusted interregional wage differentials.[33]

Our results show that Russian workers receive compensation in terms of wages for living in regions with a relatively high level of prices. The estimated coefficient of the regional price index does not significantly differ from one. This means that workers receive a 10 % wage compensation for living in a region where the price level is 10 % higher than the average price level. Dumond et al. (1999) obtained an estimate for the coefficient of the regional price level significantly lower than one (0.457) for the USA, and Roback (1988) received an estimate close to one (0.972). Such discrepancies in the estimates may be explained by whether or not housing prices are included in the regional price index. In our study and in the study of J. Roback, unlike the study of J. Dumond et al., the price index does not contain housing prices.

Russian workers also receive compensation in terms of wages for living in regions with a relatively low expected lifetime. They receive 2.1 % wage compensation for living in a region where the expected lifetime is 1 % lower than on average in the country (1 % of the average expected lifetime of 64 years amounts to about 7.5 months).[34] Such RC as the average temperature in January, the level of air pollution, the number of medical stuff per person, the unemployment level, and the number of telephones per person also have an influence on individual wages that is predicted by the theory of compensative differences.[35] The last characteristic may

[33]We note that all regional characteristics are significant at the 10 % level, and they are jointly significant at the 5 % level. As an additional robustness check, we reestimated specification 9 excluding from the sample two Russian capitals—Moscow and Saint Petersburg— which are two regions that are outliers on most of the regional characteristics used. Though this reduced the size of coefficients at medical staff and life expectancy, all the coefficients remained significant at the 10 % level.

[34]We note that high life expectancy in Russia's southern regions might be a consequence of a high proportion of people with specific religious, cultural and ethnic traditions. Therefore, it could be difficult to receive this amenity by moving to these regions. However, firstly, living in a neighborhood where people live longer might be a self-dependent amenity for migrants (for instance, from the point of view of gaining experience). Secondly, high life expectancy is not possible without favorable natural and environmental conditions.

[35]The positive relationship between wages and regional unemployment level may be also interpreted in a dynamic perspective. For instance, recent studies suggest that high unemployment regions have a higher rate of reallocation (e.g., Pastore 2012). If we assume that in regions with more intense worker reallocation and industrial restructuring wages are higher than in other regions, then we receive a positive correlation between regional wages and unemployment. However, we are not aware of studies which examine the relationship between restructuring and unemployment in Russia.

be viewed as a productive regional amenity. Its positive influence may be explained by noting that the number of telephones decreases the costs of regional enterprises.

The only variable with a sign that is counter to theoretical expectations is the crime level. The coefficient of this variable remains negative and statistically significant in all specifications. The negative relation holds even if we replace this variable by one that reflects a similar regional characteristic, e.g., the share of crimes in a region that was committed by juveniles. Perhaps the crime level should also be placed among productive regional amenities.

The results of our estimations generally agree with the results of previous studies on Russia. Berger et al. (2008) found that characteristics of cities such as the number of telephones per person, medical staff per person, the crime level, and the number of days per year when the temperature is below zero have a significant influence on individual wages. At the same time, the effect of air pollution was insignificant and the influence of the crime level was negative in this study. Bignebat (2005) found that the regional price level, the air pollution level, and regional number of hospital beds (as an analog of our variable, medical staff per person) have the influence on individual wages that is predicted by the theory of compensative differences. However, the average temperature in January was insignificant. It should be emphasized that it is hard to draw any robust conclusions from the comparisons of results of our study and previous studies. Unlike our study, they used RLMS micro-data and their methodology was quite different from ours. Nevertheless, it should be mentioned that our analysis has a number of advantages, because it is based on NOBUS micro-data that is more suitable for considering regional labor markets and also uses a more correct methodology.

Government Regional Wage Coefficients How these findings change if we control for the government regional wage coefficients? Results of the estimation of the Specification 9 with the regional coefficients are presented in Column 11 of Table 4.8. First of all, the coefficients of all RC remained significant. Moreover, they almost have not changed.[36] This suggests that the compensation mechanism estimated above functions in spite of the existing government system of wage coefficients. At the same time, it turned out that the regional wage coefficients themselves are not correlated with individual wages. However, if we keep only regional wage coefficients and do not include all other regional variables, then regional wage coefficients are positively correlated with wages. This means that wage compensations generated by market forces cover compensations by the government.

Compensations and Different Types of Workers The estimation results for our final specification (Specification 9) for groups of workers with different level of mobility are presented in Table 4.9. We emphasize two general findings. Firstly, the signs

[36]The estimated coefficient of the regional price index became lower, but it still does not significantly differ from one (the p-value of the F(1,78)-statistics of the corresponding F-test is equal to 0.379). Changes in other coefficients are not significant either.

Table 4.9 Estimation of final specification (9) for subgroups of workers

	Age and children		Education	
Criteria	15–29, with children	15–29, without children	Secondary	Higher
Price index (ln)	1.029** (0.119)	0.945** (0.130)	0.905** (0.125)	0.900** (0.109)
Life expectancy (ln)	−1.724** (0.559)	−2.601** (0.770)	−1.631** (0.676)	−2.040** (0.624)
Average temperature in January (°C)	−0.013** (0.004)	−0.022** (0.005)	−0.019** (0.005)	−0.021** (0.005)
Crime rate (per 1,000 citizens)	−0.008** (0.003)	−0.016** (0.005)	−0.012** (0.004)	−0.015** (0.005)
Air pollution (1,000 tons per 1 km^2)	0.086** (0.136)	0.105** (0.027)	0.115** (0.017)	0.130** (0.019)
Medical staff (per 10,000 citizens)[a]	−0.001 (0.002)	−0.004* (0.002)	−0.003 (0.002)	−0.002 (0.002)
Stationary telephones (per 1,000 citizens)[a]	0.002 (0.002)	0.002 (0.002)	0.003 (0.002)	0.002 (0.001)
Regional unemployment level (ln)	0.054 (0.062)	0.160 (0.102)	0.092 (0.079)	0.145** (0.052)
Control for migration costs	Yes	Yes	Yes	Yes
Constant	4.013 (2.639)	7.967** (3.104)	5.044 (2.952)	6.333* (2.714)
R^2	0.506	0.477	0.515	0.433
No. of observations	5,229	5,773	9,365	9,999

Comments: Standard errors robust to heteroscedasticity and clustering are in parentheses
*Coefficient is insignificant at the 5 % level
**Coefficient is significant at the 1 % level
[a]These variables were instrumented by their own values for 1990

of the coefficients of the RC estimated on subsamples are the same as for the whole sample of workers. Secondly, the magnitude of wage compensation for all regional disamenities is higher for more mobile groups of workers (young workers without children and workers with higher education) than for less mobile groups. Such a finding is completely consistent with the theoretical predictions: more mobile workers will receive on average a higher level of wage compensation, because they are able to choose from a wider set of "wage–amenity" pairs. At the same time, the magnitude of wage compensation for regional price level is lower for more mobile groups than for less mobile groups. A similar result was reported in the study of Dumond et al. (1999) for the USA. Generally, we conclude that the results we obtained for different groups of workers agree with the results obtained for the whole sample of workers and generally conform to the predictions of the theory of compensating differences.

Adjustment of Interregional Wage Differentials Next, we adjust the interregional wage differentials for differences in the regional employment composition and significant RC. The adjustment was carried out on the basis of Specification 9. Detailed results of adjustment for all regions are presented in Table 4.10. We emphasize two general findings.

The first one is that a broadening of the set of factors smoothes interregional differentials, and as a result both measures of regional wage dispersion—WASD and WMAD—decline by about 70 %. Therefore, our analysis offers two explanations for the interregional variation in wages. The first one refers to cross-regional differences in composition of the employment. The second relies on the theory of compensating differences. Unfortunately, it is hard to directly compare the effects of each of these explanations into interregional wage differentiation. Their relative impacts depend on sequence in which the corresponding factors are introduced in the regression. However, we can compare the shares of explained variation due to adding a variable after all other variables have been taken into account. Implementing this method, we receive that the impact of the whole set of regional variables is much higher than that of the employment composition (more than 50 % against approximately 15 % of the explained variation). Moreover, an impact of any regional characteristic exceeds an impact of any element of the employment composition.[37] These results show that the RC used are of more importance for the explanation of interregional wage differentials than regional employment compositions.[38]

[37] Among the elements of the employment composition, the industrial mix plays the most important role contributing about 8 % of IWD (for more details see Oshchepkov 2009).

[38] Within the framework used in our paper, we implicitly treat employment composition as fixed. However, at each moment differences in the employment composition across regions are subject to the ongoing and uneven process of industrial restructuring. Therefore, in several years the impact of employment composition may rise (or fall). In order to investigate our results in such a dynamic perspective, we need regionally representative panel micro-data, which are not available.

Table 4.10 Adjustment of interregional wage differentials

	% of regional employment compared to national employment	Unadjusted deviations	Deviations adjusted for differences in employment composition (*X*)	Deviations adjusted for differences in employment composition (*X*), significant regional characteristics (RC), and migration costs (on the basis of Specification 9)
Belgorod Region	0.882	−0.428	−0.184	0.114
Bryansk Region	**0.853**	**−0.412**	**−0.274**	**0.018**
Vladimir Region	1.229	−0.151	−0.103	−0.011
Voronezh Region	**1.455**	**−0.312**	**−0.191**	**−0.085**
Ivanovo Region	**0.855**	**−0.345**	**−0.209**	**0.101**
Kaluga Region	0.907	−0.129	−0.064	−0.093
Kostroma Region	**0.522**	**−0.272**	**−0.109**	**−0.029**
Kursk Region	0.877	−0.488	−0.227	−0.045
Lipetsk Region	**0.794**	**−0.207**	**−0.101**	**0.054**
Moscow Region	5.109	0.482	0.398	0.147
Orlov Region	**0.583**	**−0.385**	**−0.207**	**0.053**
Ryazan Region	0.745	−0.083	−0.02	0.071
Smolensk Region	0.836	−0.243	−0.118	0.012
Tambov Region	**0.684**	**−0.404**	**−0.264**	**−0.096**
Tver Region	**1.172**	**−0.162**	**−0.026**	**0.101**
Tula Region	1.212	−0.218	−0.154	−0.147
Yaroslavl Region	**1.075**	**−0.041**	**−0.003**	**0.155**
Moscow	**7.662**	**0.638**	**0.201**	**−0.072**
Republic of Karelia	0.62	0.423	0.386	0.189
Republic of Komi	**0.8**	**0.271**	**0.31**	**−0.145**
Arhangelsk Region	**1.068**	**0.09**	**0.196**	**−0.023**

Vologda Region	1.006	−0.092	0.131	0.091
Kaliningrad Region	0.717	0.005	0.082	0.100
Leningrad Region	1.356	0.329	0.383	0.066
Murmansk Region	**0.846**	**0.477**	**0.494**	**−0.057**
Novgorod Region	**0.526**	**−0.155**	**−0.04**	**−0.075**
Pskov Region	**0.488**	**−0.345**	**−0.195**	**−0.168**
Saint Petersburg	**4.308**	**0.564**	**0.146**	**0.163**
Republic of Adigeya	**0.233**	**−0.382**	**−0.243**	**0.139**
Republic of Dagestan	**0.809**	**−0.55**	**−0.383**	**0.191**
Republic of Ingushetia	0.103	−0.008	0.065	0.452
Republic of Kabardino-Balkarskaya	**0.338**	**−0.415**	**−0.289**	**0.052**
Republic of Kalmykia	0.175	−0.677	−0.312	0.180
Republic of Karachaevo-Cherkessia	0.229	−0.389	−0.279	0.045
Republic of North Ossetia	0.414	−0.299	−0.246	0.167
Krasnodars Region	**3.106**	**−0.254**	**−0.09**	**0.011**
Stavropol Region	1.517	−0.472	−0.25	−0.137
Astrahan Region	**0.646**	**−0.325**	**−0.217**	**0.224**
Volgograd Region	**1.653**	**−0.299**	**−0.235**	**−0.113**
Rostov Region	**2.603**	**−0.315**	**−0.215**	**−0.018**
Republic of Bashkortostan	**2.647**	**−0.14**	**−0.128**	**0.050**

(continued)

Table 4.10 (continued)

	% of regional employment compared to national employment	Unadjusted deviations	Deviations adjusted for differences in employment composition (*X*)	Deviations adjusted for differences in employment composition (*X*), significant regional characteristics (RC), and migration costs (on the basis of Specification 9)
Republic of Mari-El	0.495	−0.554	−0.289	−0.203
Republic of Mordovia	**0.554**	**−0.512**	**−0.345**	**−0.088**
Republic of Tatarstan	**2.73**	**−0.184**	**−0.209**	**0.120**
Republic of Udmurtia	**1.218**	**−0.256**	**−0.143**	**0.062**
Republic of Chuvashia	1.053	−0.582	−0.433	−0.174
Kirov Region	**1.116**	**−0.325**	**−0.141**	**0.013**
Nizhegorodskaya Region	**2.558**	**−0.257**	**−0.285**	**−0.282**
Orenburg Region	1.507	−0.479	−0.301	−0.124
Penza Region	0.784	−0.498	−0.322	−0.154
Perm Region	2.191	−0.078	−0.07	−0.013
Samara Region	**2.199**	**0.019**	**−0.1**	**−0.021**
Saratov Region	1.713	−0.464	−0.425	−0.259
Ulyanovsk Region	0.858	−0.266	−0.254	−0.111
Kurgan Region	**0.653**	**−0.363**	**−0.17**	**0.053**
Sverdlov Region	**3.267**	**0.065**	**0.03**	**0.037**
Tumena Region	**2.402**	**0.659**	**0.627**	**0.086**
Chelyabinsk Region	**2.596**	**−0.016**	**−0.099**	**−0.051**
Republic of Altai	0.13	0.017	0.167	0.343
Republic of Buryatia	**0.601**	**−0.083**	**0.059**	**−0.065**
Republic of Tyva	0.109	−0.317	−0.028	−0.221
Republic of Khakassia	0.376	−0.2	−0.063	0.064
Altai Region	1.566	−0.431	−0.211	−0.054

Krasnoyarsk Region	**2.175**	**0.21**	**0.296**	**−0.087**
Irkutsk Region	1.953	0.238	0.279	0.085
Kemerov Region	**1.846**	**0.038**	**−0.002**	**−0.080**
Novosibirsk Region	**1.845**	**−0.057**	**−0.168**	**0.000**
Omsk Region	**1.181**	**−0.305**	**−0.335**	**0.075**
Tomsk Region	0.84	−0.009	0.08	−0.119
Chitin Region	**0.719**	**−0.045**	**0.115**	**0.046**
Republic of Saha (Yakutia)	**0.655**	**0.547**	**0.624**	**−0.083**
Primorski Region	**1.499**	**0.164**	**0.206**	**−0.013**
Khabarovsk Region	**1.143**	**0.349**	**0.332**	**0.141**
Amur Region	**0.679**	**0.02**	**0.146**	**−0.021**
Kamchatka Region	**0.298**	**0.629**	**0.631**	**0.275**
Magadan Region	0.182	0.355	0.43	0.049
Sakhalin Region	**0.443**	**0.41**	**0.447**	**0.151**
Jewish Autonomous Region	0.142	−0.258	0.071	0.065
Chukotka Autonomous Region	0.063	0.933	1.176	0.227
WSD		0.371	0.258	0.114
WMAD		0.31	0.216	0.092

Comment: Regions where the NOBUS sample is representative are marked by bold

The second general finding is that the geography of regional wage premiums totally changes after adjusting for different employment compositions and significant RC. Adjusting for employment structure considerably decreases the high wage premiums in the largest Russian cities, Moscow and Saint Petersburg, where both highly paid jobs and workers with a high level of human capital are concentrated. In contrast, wage premiums in traditionally low-paid regions of the Russian South (for example, the Republics of Dagestan and Adygeya) increase. Further adjustment for significant RC (from Specification 9) improves the situation in the southern regions of Russia. A relatively high life expectancy, low prices, and low levels of air pollution characterize these regions. The relative favorableness of these regions compensates for the lower (nominal) wages. Quite to the contrary, adjusting for RC lowers the wage premiums in the northern regions [e.g., in the Murmansk and Sakhalin Regions and in the Republic of Sakha (Yakutiya)], where the price level is high and the life expectancy is low.

Adjusting for living costs and regional disamenities leads to a negative (!) wage premium in Moscow. The high level of prices and air pollution contribute to this result, but it goes contrary to the fact that Moscow is a center of attraction for migrants. It may be the case that some RC were neglected in our analysis.[39] Moscow is the capital of the country, where the headquarters of leading Russian enterprises, the central offices of many foreign companies, and the federal bodies of executive power and legislature are located. Another possible factor is the agglomeration effects of a large city (higher productivity, lower transaction costs, economy of scale, etc.), which allow firms to pay higher wages. Migrants may be also attracted to the capital city by better potential opportunities and careers.[40]

It may be expected that the adjustment presented above does not take into account some RC that are valuable for workers. Some limitations are also imposed by the fact that the NOBUS sample is not representative for about 30 Russian regions; this also adversely affects the calculation of adjusted wage premiums for regions where the NOBUS sample is representative. Therefore, it is clearly not correct to interpret the obtained estimates as recommendations for choosing a region, where people live relatively "well." Nevertheless, we argue that it is not correct to draw conclusions on the well-being of people living in different regions by comparing nominal or even real regional wages. Many other RC need to be taken into account.

Regional Wage Premiums and Net Migration It is natural to test the credibility of our results by establishing the correspondence between them and interregional migration flows. The correlation between the coefficients of net in-migration and unconditional (observed) wage premiums turned out to be negative (see Table 4.11),

[39] Although we control the size of settlement in our regressions, Moscow (as well as St. Petersburg) may demand a special treatment, because they differ from other cities in the top category (one million people or more).

[40] It may be also the case that relatively highly paid workers underrepresented more in the Moscow subsample of the database used than in the subsamples for other regions.

Table 4.11 Correlations between wage premiums and net migration coefficients

Wage premiums	2000	2001	2002	2003	2004	2005
Unadjusted	−0.111	−0.205	−0.242*	−0.276*	−0.159	−0.070
Adjusted for employment composition	−0.173	−0.391*	−0.411*	−0.419*	−0.301*	−0.215*
Adjusted for employment composition and significant regional characteristics (Specification 11)	0.310*	−0.033	0.027*	−0.066	0.004	0.033

Comments: (1) Net migration coefficient is the difference between inflows and outflows divided by the average regional population. Data on migration is taken from the statistical yearbooks "Regioni Rossii" published by Rosstat
*Coefficient is significant at the 5 % level

i.e., the lower the wage premium in a region, the higher the migration rate to this region.[41] The correlation remains negative, and its significance even rises, after adjusting for regional differences in employment composition. However, further adjustment of regional wage premiums for valuable RC makes the correlation positive. In other words, the sign of the correlation changes from the counterintuitive to what is theoretically predicted after adjustments. This suggests that migrants making decisions on where to move consider not only (nominal) regional wages but also other RC. This completely satisfies the predictions of the theory of compensating differences.

4.5 Conclusion

In this chapter, we provide evidence on compensating differences in the labor market from the largest transition economy, Russia. We apply the theory of compensating differences to wage differentials across Russian regions. Using the NOBUS micro-data and a methodology based on the estimation of the wage equation augmented by aggregate RC, we show that these differentials have a compensative nature. Russian workers receive wage compensations for living in regions with a higher price level and worse nonpecuniary characteristics, such as a relatively low life expectancy, a high level of air pollution, poor medical services, a colder climate, and a higher unemployment level. After adjusting for these RC, regional wages become positively correlated with interregional migration flows.

We emphasize that the revealed compensation mechanism has a market nature; it works even if one take into account the existing government system of regional wage

[41] Adjusted and unadjusted wage premiums tend to be relatively stable in time. Therefore, wage premiums estimated for 2003 may influence migration decisions in other years. We present correlations between adjusted and unadjusted wage premiums for the period 2000–2005.

coefficients. According to our estimates, half of the interregional wage variation between workers with similar productive characteristics should be considered as compensative. Therefore, our results show that the concept of compensative differences is appropriate for explaining interregional wage differences in Russia.

Such conclusions are relatively new and unusual for transition economies. In our view, Russian specifics are associated with the historical fact that the same regions are characterized by unfavorable living conditions and a high concentration of enterprises with a high level of profitability (above all, enterprises belonging to the extracting and exporting industries). Consequently, on the one hand, there is a need for compensation, and on the other hand, there are the resources to pay it. Therefore, interregional wage differentials in Russia have a compensative character in spite of high MC.

Although our findings are based on the analysis of data for only 1 year (2003), there are reasons to expect that the compensation mechanism has a long-run nature. Firstly, the convergence of regional average wages is rather slow, and the relative ranking of Russian regions in wage levels does not change much over time (e.g., according to the Rosstat data, correlation between regional average wages in 2003 and in 2009 is almost 0.9). A fortiori, relative positions of regions in most amenities and disamenities are stable (e.g., correlation between regional life expectancies in 2003 and in 2009 is almost 0.95!). This means that relative attractiveness of regions changes very slowly over time. Secondly, immediate movement between regions is not possible due to various reasons, and migration decisions are naturally prolonged in time. Probably, in transition economies they are prolonged even more than in developed countries.[42] Therefore, adjusted wage premiums estimated by us for 2003 influence migration decisions in other years.

Our analysis suggests some policy implications. As only a small part of the variation in nominal wages translates to differences in real well-being, policy measures oriented at the reduction of interregional wage differentials will have only a limited welfare effect. We support the view that the best policy reaction to the observed high level of interregional wage differentials should be the removal of migration barriers and a reduction in MC. This would contribute to the growth in the level of wage compensations for workers living in regions with relatively unfavorable living conditions. Welfare growth could be achieved in this case even in spite of a possible rise in the interregional differentials in nominal wages.

At the same time, our results indicate that the search for other explanations for the phenomenon of interregional wage differentials in Russia should be continued. In the framework of the theory of compensative differences, a broader set of RC, which are potentially important for workers and influence migration decisions, should be considered. One should also pay more attention to productive regional amenities that allow firms to pay wage compensations.

[42] Fidrmuc (2004) and Kwon and Spilimbergo (2005).

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Biography

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Chapter 5
Convergence Across Regions in Kazakhstan

Alisher Aldashev

Abstract This chapter analyzes unequal regional development in Kazakhstan. Applying the nonlinear least squares (NLS) method in presence of spatial correlation, we estimate the convergence rate of wages across Kazakh regions for the period 2003–2009. The estimated convergence rate is about 3.5 % which is somewhat higher than the estimates obtained for the USA and Europe implying that half of the gap between regions is reduced in about 20 years. We do not find any significant effect of resource abundance on growth. However, human capital is an important factor contributing to growth. Our estimates indicate that a 1 % increase in the share of students increases the growth rate by 0.18 % points.

Keywords Artificial regression • Convergence • Kazakhstan • Nonlinear least squares • Spatial correlation

JEL classification: O47, P25

5.1 Introduction

Compared to other former Soviet economies, Kazakhstan is one of the most successful examples of transition from the planned to the market economy. The country has been growing at the rate of 9–10 % in the 2000s prior to the world financial crisis. International Institutions (World Bank 2004; Kohl et al. 2005) give much emphasis to economic growth as a critical component of poverty alleviation. Moreover, World Bank (2004) argue that policies which promote faster growth are

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likely to be pro-poor in the long run.[1] Nevertheless, despite its admirable economic performance, Kazakhstan is going through very uneven regional development: the booming new capital Astana, the financial center and the old capital Almaty, and oil-rich regions at the shores of the Caspian Sea on the one hand, and depressed regions in the north and south on the other. Tables 5.4 and 5.5 show immense differences in per capita GRP and wages. Even more so, due to its sheer geographical size (ninth largest country in the world) and low population density combined with relatively poor infrastructure, uneven regional development might persist.[2]

The goal of this chapter is the analysis of inequality in regional development in Kazakhstan and possible convergence in incomes in particular. Using a detailed dataset disaggregated at the *raion* level,[3] we apply the nonlinear least squares (NLS) method controlling for spatial correlation to show that wages across regions converge at the pace of around 3.5 %. These results are consistent with the predictions of the basic Solow model that poorer regions will eventually catch up with the richer regions. The estimated rate of convergence is higher than the estimates for the USA and Europe reported by Barro and Sala-i-Martin (1991). The numbers imply that half of the gap between regions is reduced in about 20 years. The extensions of the basic model show that resource abundance is not a significant contributor to growth. However, inclusion of the share of university students in the population shows the importance of human capital to growth. Our estimates indicate that a 1 % point increase in the share of students increases the growth rate by 0.18 % points.

5.2 Literature Review

Beginning with the Solow (1956) seminal paper, the neoclassical growth model with decreasing returns to capital has been very popular among the economists. In its simplest form, the production function is assumed to be Cobb–Douglas with the constant returns to scale property: $Y = A \cdot K^{\alpha} L^{1-\alpha}$ with $\alpha < 1$ ensuring decreasing returns to factors of production. Given the same structural variables, the model implied faster growth for countries with lower initial GDP per capita. It was shown (see Barro and Sala-i-Martin 1990, 1991; King and Rebelo 1993) that the neoclassical growth model can be approximated as:

$$(1/T)\log(y_{it}/y_{i,t-T}) = x_i^* + \log(\hat{y}_i^*/\hat{y}_{i,t-T})(1 - e^{-\beta T})/T + u_{it}, \tag{5.1}$$

[1]Given a large share of growth driven by the oil sector, there are doubts whether the growth will indeed be pro-poor.

[2]For example, regional poverty rates varied from 2 to 32 % in 2002 (World Bank 2004).

[3]Equivalent to the European NUTS-3 level.

where y_{it} is per capita output at time t in a country i, x_i^* is the steady-state per capita growth rate, $\hat{y}_i^*$—is the steady-state level of output per effective worker, T is the length of the observation period, β is the rate of convergence, and u_{it} is the error term.[4] As $\hat{y}_i^*$ is unobserved an empirical version of Eq. (5.1) becomes[5]:

$$(1/t)\log(y_{it}/y_{i,0}) = a + x_i - (1 - e^{-\beta t})\log y_{i0}/t + \epsilon_{it}, \qquad (5.2)$$

with a being the common intercept which corresponds to the steady-state per capita growth rate, x_i are the cross-sectional fixed effects introducing the possibility that regions differ in their steady-state per capita growth rates. If $\beta > 0$, then regions with lowest per capita output grow at a higher rate. This is what is called β-convergence.

A different empirical measure of convergence is the so-called σ-convergence. It measures cross-sectional variation in a variable of interest (e.g., the output or the GDP per capita) over time. The σ-convergence is usually measured by coefficient of variation (cross-sectional standard deviation of the variable of interest normalized by the mean). Although closely linked, the two concepts (β and σ-convergence) are different. Whereas in a standard neoclassical growth model, the β-convergence is implied by diminishing returns to factors of production; σ-convergence could be driven by external shocks to the production function (see Barro and Sala-i-Martin 1991).

Much empirical work on growth was based on regression of the GDP growth rates on the initial levels of the GDP (Eq. (5.2)) and estimation of the β coefficient. Barro and Sala-i-Martin (1991) analyzed convergence across states in America and NUTS-2 regions in Europe. The results of the authors suggest that poorer regions both in the United States and in Europe grow faster than the rich ones, so the β-convergence is observed. Moreover, the estimates indicate that the average rate of convergence is about 2 % a year both in the USA and in Europe implying that the gap between the poor and rich regions shrinks at 2 % a year.

Marelli and Signorelli (2010) estimated the growth model on European data on NUTS-3 level and found convergence between the transition European countries. On the other hand, the authors showed that within each country, divergence prevailed, so that certain regions with high initial GRP per capita grew faster than the rest of the country. Regional divergence in Central European countries has been documented by several authors (Huber 2007; Römisch 2003; Solanko 2003). The data show that variation in wages and GRP per capita has been rising in the Central European countries. The growth patterns for different post-communist European economies suggest convergence of agricultural regions, although shares of employment in agriculture have negative impact on growth (Huber 2007, and citations therein).

[4]For an empirical specification which includes human capital see Mankiw et al. (1992).

[5]Barro and Sala-i-Martin (1991).

5.3 Data and Methodology

Kazakhstan has vast territory spanning over about 2.7 million sq. km. Administratively, the country is divided into 14 regions (*oblasts*) and 2 cities (the new capital Astana and the old capital Almaty).[6] Each *oblast* is further divided into *raions*.[7] The data of the National Statistical Agency of Kazakhstan on *oblast* level reveals huge differences in such indicators as the GRP per capita and the nominal monthly wage. The GRP per capita and the monthly wage in 2009 spread from the lowest 336.3 and 44.0 thousand Tenge,[8] respectively in Zhambyl *oblast* (a region in the South of Kazakhstan) to the highest 3381.6 and 129.0 thousand Tenge in Atyrau (a region at the shores of the Caspian Sea).[9]

To test the β-convergence hypothesis, one could estimate Eq. (5.2). One has to note that this model is nonlinear in parameters. However, for a nonlinear model $y = x(\beta) + u$, the moment condition is $\mathbf{X}'(\beta)(y - x(\beta)) = 0$, with $\mathbf{X}(\beta)$ being a matrix containing the first derivatives of the regressor matrix, x, with respect to the parameter vector β evaluated at x. The parameter vector estimated given this moment restriction is the NLS estimator and is close to the method of moments estimator (see Davidson and MacKinnon 1993).

One has to bear in mind that regions are not isolated units and hence interact with each other. Regional spillover effects[10] can result in correlation of regression residuals across spatial units (see Anselin 2000). The standard errors could be corrected for cross-sectional correlation using the method of Driscoll and Kraay (1998). The method is in principle an extension of the GMM estimator of Newey and West (1987). In a simple univariate model, $y_{it} = x_{it} + \epsilon_{it}$ with spatial but no time dependence, the identifying moment restriction is $E(x_{it}\epsilon_{it}) = 0$. Driscoll and Kraay (1998) show that the variance matrix is given by:

$$\mathbf{Var} = (\mathbf{X}'\mathbf{X})^{-1} S_T (\mathbf{X}'\mathbf{X})^{-1}, \tag{5.3}$$

where $S_T = \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N}\sum_{j=1}^{N} E(x_{it}\epsilon_{it}x_{jt}\epsilon_{jt})$ (see also Hoechle 2007). The method works, however, in the linear case. To correct standard errors in the nonlinear model, one could run a linear artificial regression:

$$r(\hat{\beta}) = \mathbf{X}(\hat{\beta})b + \text{res}, \tag{5.4}$$

where $r(\hat{\beta})$ are residuals from the NLS regression evaluated at the estimated parameter value $\hat{\beta}$, $\mathbf{X}(\hat{\beta})$ is the matrix of first derivatives of x evaluated at the

[6] Equivalent to the European NUTS-1 or NUTS-2 level of aggregation.

[7] Equivalent to the European NUTS-3 level.

[8] 1 USD is worth roughly 150 Tenge.

[9] see Tables 5.4 and 5.5.

[10] For example, growth of income in one region increases demand and thus may increase output and income in another region. Furthermore, differences in incomes generate migration flows which affect income differentials.

estimated parameter value $\hat{\beta}$ and b is the coefficient vector, and res is the residual which has no further interpretation (see Davidson and MacKinnon 2000). The estimated covariance matrix of b is an estimator of the covariance matrix of β. Applying the method of Driscoll and Kraay (1998) on the linear regression in Eq. (5.4) gives the consistent estimator of the covariance matrix of β.

Equation (5.2) has been estimated using the yearly panel of *raions* of Kazakhstan using the NLS method described above. Unfortunately, the data on the GRP is unavailable at this level of aggregation. For this reason, the monthly wage was chosen as a proxy for the per capita income. For competitive markets, the real wage is the marginal product of labor, which, given the production function specified in Sect. 5.2, becomes $(1-\alpha)A \cdot k^{\alpha}$. Given the assumption of diminishing marginal product of capital, wages also converge to the steady-state levels (see table 5.5 in appendix).

Nominal wages were converted into real wages using the CPI estimates of the Statistical Agency of Kazakhstan on *oblast* level. The time dimension of the panel is 10 years (2002–2011), but given that we estimate the growth rate or changes it leaves us with 8 periods and 1,782 observations.

The average growth rate in the sample is about 10 % ranging from lowest 36 % to highest 44 with the standard deviation of 5 % points. There is also high variation in salaries in the sample. The mean salary is 36.6 thousand Tenge with the standard deviation of about 24 thousand. The lowest observed salary is 7,078 and the highest is 198 thousand Tenge (see table 5.4 in appendix).

The average salary growth rates are plotted against initial salary in Fig. 5.1. The illustration supports the convergence hypothesis implied by the neoclassical growth model (Table 5.1).

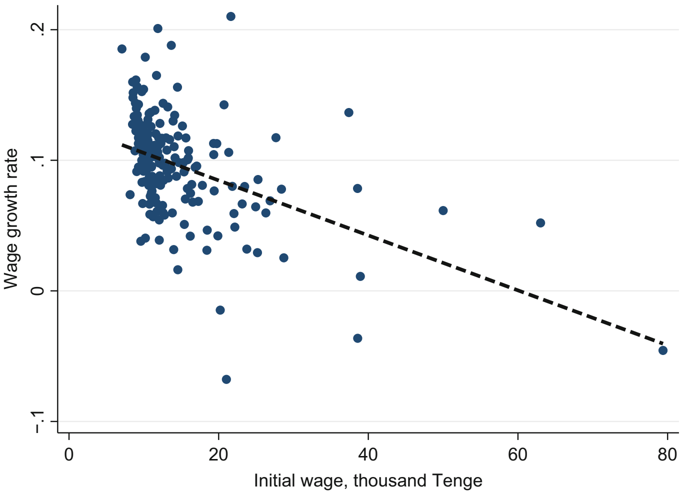

Fig. 5.1 Convergence across regions. (**a**) Own calculations based on Kazakhstan statistical agency data. (**b**) 2003–2007 is shown by *triangles* and a *solid line* (linear regression line). (**c**) 2008–2011 is shown by *crosses* and a *dashed line* (linear regression line)

Table 5.1 Nominal and real monthly wages and GDP growth

Year	Nominal wage (in Tenge)	Nominal wage (in USD)	Real wage (in percent to previous year)	Real GDP growth rate (in percent)
2003	23,128	155	107.0	9.2
2004	28,329	208	114.6	9.1
2005	34,060	256	111.7	9.5
2006	40,790	324	110.3	10.6
2007	52,479	428	116.1	8.5
2008	60,805	505	99.0	2.4
2009	67,333	456	103.2	1.2
2010	77,611	527	107.6	7.0
2011	90,028	614	107.1	7.5
2012	101,263	679	107.0	5.5

Columns 2–4: National statistical agency of Kazakhstan; column 5: CIA world factbook

5.4 Results

Estimation results of Eq. (5.2) are presented in Table 5.2. Columns 2 and 3 contain the parameter and standard error estimates from Eq. (5.1) excluding the *oblast* fixed effects thereby imposing absolute convergence restriction. Columns 4 and 5 contain the parameter and standard error estimates of the same model but including the *oblast*-specific fixed effects and thus implying that each *oblast* may converge to its own steady-state growth rate.

The results reveal that inclusion of *oblast* dummies did not change the estimate of the rate of convergence.[11] The estimate of $\beta = 0.035$ implies that the convergence rate is 3.5 % per year which is higher than estimates for the USA and Europe (Barro and Sala-i-Martin 1991, report 2 % rate of convergence). According to this estimate half of the initial wage gap disappears in about 20 years, and it will take some 40 years to eliminate 75 % of the gap.

The significance of *oblast* dummies implies that each *oblast* converges to its unique steady-state growth rate. Authors emphasize the importance of industry structure and openness of the economy (Barro and Sala-i-Martin 1991) and human capital (Mankiw et al. 1992; Higgins et al. 2006). In light of these arguments, we extend the model in Eq. (5.2) to include the dummy for regions with large oil and gas reserves[12] and the share of university students in total population.[13] The results of modified regressions are presented in Table 5.3. As a robustness check, we also

[11]Regional dummies appear to be statistically significant. Estimates for the dummy variables are not reported but are available from the author upon request.

[12]Regions where top ten oil and gas deposits are located.

[13]Usually authors would include the share of university graduates. However, this information is unavailable. Moreover, the information on university students is unavailable on the *raion* level and hence, we had to use the shares of university students on the *oblast* level.

Table 5.2 β-convergence estimation; Dependent variable—monthly wage growth

Variable	Coeff.	St.error	Coeff.	St.error	Coeff.	St.error	Coeff.	St.error	Coeff.	St.error	Coeff.	St.error
β	0.030	0.006	0.052	0.004	0.032	0.003	0.029	0.006	0.052	0.005	0.033	0.004
a	0.359	0.048	0.554	0.034	0.369	0.023	0.366	0.052	0.570	0.042	0.378	0.030
Oblast dummies	No		No		No		Yes		Yes		Yes	
Time period	2003–2011		2003–2007		2008–2011		2003–2011		2003–2007		2008–2011	
R^2	0.08		0.11		0.22		0.13		0.17		0.31	
N	1,782		990		792		1,782		990		792	

NUTS3 level (standard errors are corrected for spatial correlation)

Table 5.3 The effect of oil reserves and education on growth; dependent variable—monthly wage growth

Variable	Coeff.	St.error	Coeff.	St.error	Coeff.	St.error	Coeff.	St.error	Coeff.	St.error	Coeff.	St.error
β	0.026	0.007	0.050	0.008	0.034	0.004	0.026	0.007	0.048	0.008	0.035	0.004
a	0.333	0.060	0.539	0.062	0.377	0.027	0.332	0.058	0.533	0.062	0.390	0.030
Oil dummy	0.015	0.014	0.043	0.020	0.010	0.003	0.008	0.012	0.036	0.017	0.004	0.003
Share of $R\&D$ in GRP	−0.001	0.004	0.004	0.005	0.000	0.001	0.014	0.003	0.013	0.004	0.020	0.005
Oblast dummies	No		No		No		Yes		Yes		Yes	
Time period	2003–2011		2003–2007		2008–2011		2003–2011		2003–2007		2008–2011	
R^2	0.11		0.18		0.23		0.19		0.27		0.31	
N	1,782		990		792		1,782		990		792	

NUTS3 level (standard errors are corrected for spatial correlation) repeated the exercise excluding Almaty (the former capital) and Astana (the new capital) from the sample. The results are, however, unchanged.[14]

The dummy for oil and gas regions is statistically insignificant. Hence, the steady-state growth rates do not differ between oil-rich regions and the rest of the country *ceteris paribus*. This is in contrast to the usual results in the literature where resource abundant countries grow slower (see, e.g., the review in Sachs and Warner 1995). The share of university students has a significant positive effect on the growth rate. A 1 % point increase in the share of students in the population increases the growth rate by 0.18 % points. These results indicate that in case of Kazakhstan resource abundance does not contribute significantly to growth. However, human capital accumulation as measured by the share of university students in the population is an important factor contributing to growth.

5.5 Conclusion

In this chapter, we analyzed convergence of wages in Kazakhstan. Using a panel of regions (*raion* level), for a period 2003–2009 the rate of convergence in monthly wages has been estimated using a nonlinear least squares model. To correct for spatial correlation, we construct the artificial regression and apply the method by Driscoll and Kraay (1998). The estimated rate of convergence is about 3.5 % per year which is higher than the estimates for the USA and Europe reported by Barro and Sala-i-Martin (1991) implying that half of the gap between regions is reduced in about 20 years. We also find that resource rich regions do not seem to differ significantly from the rest of the country in steady-state growth rates. However, human capital is an important factor contributing to growth. Our estimates indicate that 1 % point increase in the share of students increases the growth rate by 0.18 % points.

Appendix

Wage Convergence

Given the production function $Y = A \cdot K^{\alpha} L^{1-\alpha}$, then the marginal product of labor becomes $(1-\alpha)A \cdot k^{\alpha}$, where $k = K/L$. The log wage rate is thus: $\ln w = \ln(1-\alpha) + \ln A + \alpha \ln k$. Assuming that the capital share, α, is constant over time, the growth rate of wages becomes $g_w = g_A + \alpha g_k$, where g_w is the growth rate of wages, g_A is the TFP growth rate, and g_k is the growth rate of capital-to-labor ratio. Given the diminishing marginal product of capital, the steady state exists where $g_k = 0$.

[14] Estimation results are presented in table 5.6 in the appendix.

Table 5.4 Nominal GRP, thousand Tenge

	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Kazakhstan	108.8	135.1	174.7	218.8	254.1	309.3	391.0	501.1	667.2	829.9	1,024.2	1,068.0
Akmola	53.8	96.1	105.3	140.6	155.2	189.1	222.1	263.4	340.0	543.2	641.4	709.3
Aktobe	122.3	136.7	175.2	219.7	268.7	353.2	438.1	604.9	748.1	970.5	1,231.1	1,193.1
Almaty	55.7	63.8	80.1	102.1	119.2	147.3	163.5	202.1	253.5	337.4	409.2	460.3
Atyrau	226.6	314.7	554.5	658.4	866.0	1,065.0	1,389.5	1,727.3	2,296.2	2,541.7	3,626.0	3,881.6
West Kazakhstan	87.4	124.4	195.5	249.5	296.7	333.1	589.8	659.8	838.6	1,006.2	1,339.4	1,324.2
Zhambyl	46.7	50.3	58.7	71.2	84.7	121.6	138.8	169.1	191.2	262.8	316.9	336.3
Karaganda	131.7	168.0	217.7	249.3	276.7	333.6	382.3	509.9	690.1	853.5	1,088.4	1,123.5
Kostanai	109.5	135.8	163.1	181.2	199.6	256.5	299.1	356.5	429.5	624.5	789.7	815.3
Kyzyl Orda	60.7	64.4	96.3	122.2	170.2	224.6	294.9	394.0	585.2	794.7	1,075.9	937.4
Mangistau	191.2	263.2	407.9	455.0	599.3	633.4	831.6	1,174.2	1,552.9	1,896.2	2,631.0	2,542.5
South Kazakhstan	48.9	62.0	88.3	114.1	117.1	145.8	142.7	161.7	187.6	265.2	310.4	384.8
Pavlodar	153.2	156.1	214.4	266.2	286.9	359.7	449.0	516.6	621.3	793.9	1,153.6	1,150.8
North Kazakhstan	86.4	102.9	100.4	141.7	162.2	207.1	226.7	277.9	357.8	487.4	619.0	625.5
East Kazakhstan	116.1	139.0	158.4	188.2	199.0	228.9	270.6	325.4	430.8	563.4	627.9	693.6
Astana city	186.8	262.2	328.6	438.1	463.8	596.8	901.7	1,318.0	1,701.8	1,927.0	2,080.2	2,075.2
Almaty city	265.1	319.8	367.5	504.9	603.3	695.8	924.4	1,218.6	1,792.9	2,048.9	2,193.2	2,293.1

Source: National statistical agency

Table 5.5 Average nominal monthly wage, Tenge

	2003	2004	2005	2006	2007	2008	2009	2010
Kazakhstan	23,128	28,329	34,060	40,790	52,479	60,805	67,333	77,611
Akmola	14,954	18,706	22,740	27,687	36,540	41,944	47,794	54,557
Aktobe	23,848	29,482	34,851	40,905	50,271	56,090	60,375	69,726
Almaty	15,933	20,180	24,436	29,779	39,483	44,327	49,715	58,430
Atyrau	48,338	53,472	65,195	74,682	94,373	111,023	129,009	148,310
West Kazakhstan	29,876	31,868	36,145	40,198	50,242	59,362	69,455	80,101
Zhambyl	14,779	19,131	22,542	26,750	33,996	37,546	43,951	51,340
Karaganda	19,962	24,772	28,440	34,612	44,236	53,472	57,611	66,539
Kostanai	16,803	20,693	24,431	29,249	37,584	43,903	49,130	57,268
Kyzyl Orda	19,928	26,400	30,948	36,116	46,859	53,333	60,227	69,753
Mangistau	44,369	53,832	63,959	72,086	82,055	98,743	112,907	133,148
South Kazakhstan	15,309	19,386	22,854	27,586	36,707	41,679	48,610	57,545
Pavlodar	21,801	26,872	31,062	36,882	46,297	52,227	56,113	64,955
North Kazakhstan	15,245	19,166	23,011	27,182	34,522	39,790	45,755	51,689
East Kazakhstan	20,099	23,846	27,688	33,101	42,137	48,293	53,496	61,388
Astana city	33,002	41,921	51,001	63,001	79,210	89,631	98,864	110,838
Almaty city	32,622	39,614	49,201	59,240	78,021	90,239	95,139	106,597

Source: National statistical agency

Table 5.6 The effect of oil reserves and education on growth; Dependent variable—monthly wage growth

Variable	Coefficient	St.error[a]	Coefficient	St.error[a]
β^b	0.036	0.007	0.037	0.007
a	0.417	0.059	0.414	0.056
Oil dummy	0.025	0.019	0.025	0.018
Share of univ. students (in per cent)	–	–	0.191	0.049
R^2	0.14		0.14	
N	1,372		1,372	

NUTS3 level in 2003–2009 (Excluding Almaty and Astana)
[a]Standard errors are corrected for spatial correlation
[b]Rate of convergence as specified in Eq. (5.2)

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Part II
Agglomeration Economies

Chapter 6
Agglomeration Economies and Employment Growth in Italy

Roberto Basile, Cristiana Donati, and Rosanna Pittiglio

Abstract Using local labor systems (LLSs) data, we assess the effect of the local productive structure on employment growth in Italy during the period 1981–2008. Italy represents an interesting case study because of the high degree of spatial heterogeneity in local labor market performances and of the presence of strongly specialized LLSs (industrial districts). Building on semi-parametric geoadditive models, our empirical investigation allows us to identify important nonlinearities in the relationship between local industry structure and local employment growth to assess the relative performance of industrial districts and to control for unobserved spatial heterogeneity.

Keywords Employment dynamics • Geoadditive models • Industrial districts • Industry structure • Semi-parametric

JEL Classification R11, R12, C14

6.1 Introduction

In this chapter, we analyze the effect of industry structure on local employment growth in Italy. The hypotheses put into empirical test concern the role of many factors characterizing the local productive structure: (1) the presence of an *industrial district*; (2) the level of productive *specialization*; (3) the degree of sectoral *diversification*; (4) the population *density*; (5) the level of *local competition*; and (6) the average *firm size*. In this way, we follow the broad literature started by

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Glaeser et al. (1992) and Henderson et al. (1995).[1] Previous studies carried out for the case of Italy (Mameli et al. 2008; Paci and Usai 2008) report a negative impact of specialization externalities (notwithstanding the strong anecdotal evidence of the economic success of *industrial districts*, the places where Marshallian externalities are magnified) and a positive effect of diversification on local employment growth. Only Forni and Paba (2002) find a positive impact of both specialization and Jacobs externalities.

We claim that the results of previous studies may suffer from a number of model mis-specification issues. First, all of these studies measure Marshallian (or specialization) externalities using location quotients disregarding the fact that higher specialization levels may lead higher vulnerability to idiosyncratic shocks (such as a decline faced by the primary industry of the local area) and, thus, are likely to bolster asymmetric developments and differences in growth rates across local economies, unless some effective "risk sharing" mechanisms help "protect" the local economic environment against idiosyncratic shocks (Basile and Girardi 2010). In particular a form of insurance mechanism is represented by those socioeconomic factors which contribute to determine the "industrial atmosphere" theorized by Marshall as well as by several Italian economists (e.g., Becattini 1987; Becattini et al. 2003; Bellandi 2007). In a nutshell, if we want to empirically assess the existence of Marshallian externalities, we need to bear in mind that this kind of external economies are more likely to occur within industrial districts than anywhere else.

Second, most of the previous studies disregard the existence of nonlinearities in the relationship between industry structure and employment growth. De Lucio et al. (2002), Viladecans-Marsal (2004), and Illy et al. (2011) allow for nonlinearities by introducing quadratic terms in their models. Although this is the easiest way to deal with such a nonlinearity in a parametric framework, it is only one of several possible nonlinear parameterizations. Indeed, nonlinearities can be better accommodated in a semi-parametric framework, where the actual shape of the partial effect can be assessed using smooth functions.

Third, most of these studies do not control for unobserved spatial heterogeneity when specifying the local economic growth model, disregarding the role of "first nature" characteristics of local areas (Krugman 1993) in affecting their growth performance.

Using data for 686 local labor systems (LLSs) in Italy for both manufacturing and services and for three different periods (1981–1991, 1991–2001, 2001–2008), we contribute to the existing literature (a) by assessing the presence of nonlinearities in the relationship between industry structure and local-sector employment growth, (b) by comparing the relative performance of industrial districts, and (c) by controlling for spatial heterogeneity.

[1] See also, among others, Henderson (1997), Combes (2000), Rosenthal and Strange (2004), de Groot et al. (2009), and Melo et al. (2009). For a recent review of the literature, see Beaudry and Shiffauerova (2009).

To this aim, we develop a methodological framework which innovates with respect to the existent literature along several dimensions. First, we use a semi-parametric model that allows us to identify smooth non-linear effects of the growth predictors. Second, we include in our model a dummy variable, *ID*, which takes value 1 if the LLS belongs to an industrial district and zero otherwise. Specifically, we distinguish between the within-sector and the between-sector *ID* effects. Third, exploiting the longitudinal dimension of our dataset, we include in our model a geo-additive component (a smooth interaction between latitude and longitude) for each time period which permits us to control for time-varying unobserved spatial heterogeneity.

Our empirical evidences confirm that industrial districts have performed better than the other LLSs during the sample period, thus suggesting that Marshallian externalities exerted a positive role on local employment growth. Regression results also highlight a hockey stick-shaped relationship between specialization and local employment growth: net of the industrial district' effect, a higher specialization per se reduces the employment dynamics, but only up to a certain threshold after which specialization has no effect on growth. In line with previous evidence and corroborating Jacobs' theory, diversification boosts employment growth in manufacturing and reduces it in services. Allowing for nonlinearities and in keeping with theoretical predictions, we find a hump-shaped relationship between population density and local employment growth: the positive effect of overall population density fades as the density of economic activities reaches some threshold value, after which congestion costs overcome agglomeration externalities. Nonlinear effects are also evident for local competition and average firm size. Finally, the inclusion of a smooth spatial trend surface allows us to control for spatial heterogeneity due to the first nature features of the LLS.

The remainder of the chapter is organized as follows. Section 6.2 describes our modeling strategy. Section 6.3 provides information about data and variables. The results are presented and discussed in Sect. 6.4. Conclusions are reported in Sect. 6.5.

6.2 Modeling Regional Employment Growth

6.2.1 A Review of the Literature

Combes (2000) analyzes the relationship between industry structure and local employment growth by estimating the following log-linear reduced form:

$$\begin{aligned} y_{r,s,t} = {} & \beta_0 + \beta_1 \log(\text{spe}_{r,s,t-\tau}) + \beta_2 \log(\text{div}_{r,s,t-\tau}) + \beta_3 \log(\text{den}_{r,t-\tau}) \\ & + \beta_4 \log(\text{size}_{r,s,t-\tau}) + \beta_5 \log(\text{comp}_{r,s,t-\tau}) + \gamma_s + \delta_t + \varepsilon_{r,s,t} \end{aligned} \quad (6.1)$$

where $y_{r,s,t}$ is the employment growth rate of sector s in site r computed over a given period (between $t-\tau$ and t); $\text{spe}_{r,s,t-\tau}$, $\text{div}_{r,s,t-\tau}$, $\text{den}_{r,t-\tau}$, $\text{size}_{r,s,t-\tau}$, and $\text{comp}_{r,s,t-\tau}$ are the explanatory variables computed at the initial period $t-\tau$ and corresponding respectively, to specialization, diversity, population density, average size of plants, and local competition; β_0-β_5 are the parameters associated to the intercept and to the explanatory variables expressed in log terms; γ_s is a sector fixed effect; δ_t is a temporal fixed effect; and $\varepsilon_{r,s,t}$ is an error term assumed to be *iid*.[2] The variable *spe* should capture external economies which may occur among firms producing similar goods or services and operating in the same area. According to the Marshall–Arrow–Romer theory (the MAR-theory), formalized by Glaeser et al. (1992), within-sector pecuniary (static) and nonpecuniary (dynamic) externalities (knowledge spillovers) are the main sources of local growth. These external economies are known as *localization* or *specialization externalities* and are often measured with the degree of *sectoral specialization* of the region. Therefore, according to the MAR theory, the higher the degree of specialization of the region in a specific industry, the higher the growth rate in that particular industry within that region.

From a different perspective, Jacobs (1969) argues that the most important sources of pecuniary and nonpecuniary economies are external to the industry within which the firm operates. She suggests diversity rather than specialization as a mechanism leading to economic growth: a diverse sectoral structure increases the chances of interaction, generation, replication, modification, and recombination of ideas and applications across different industries; moreover, a diverse industrial structure protects a region from volatile demand and offers it the possibility of switching between input substitutes. *Urbanization* or *Jacobs externalities* are measured with the degree of *sectoral diversification* (*div*) of the local production structure. According to Jacobs theory, the higher the degree of diversification of the region, the higher its growth rate.

Empirical evidence provided by a large amount of studies in support of the Marshall and Jacobs theories yields mixed results. Beaudry and Shiffauerova (2009) review 67 studies and discuss their basic results. According to them, almost half of these studies report both MAR and Jacobs externalities. Both specialized and diversified local industrial structures may, therefore, be conductive to local economic growth. In line with this interpretation, Duranton and Puga (2000, p. 553) observe that there is “a need for both large and diversified cities and smaller and more specialized cities”. Although positive evidence for both types of externalities is reported, many of these studies also find negative impacts. However, the negative influence is observed much more often for Marshallian externalities than for Jacobs externalities (only in 3 % of all the studies). For the case of Italy,

[2] A similar specification has been used by Paci and Usai (2008) and Mameli et al. (2008). These authors also extend this model by introducing other explanatory factors (such as human and social capital) into the model framework, but they conclude that the baseline model (1) does not suffer from problems connected to omitted variables. On the basis of these evidences and because of the lack of complete information on further explanatory variables for the whole sample period, we do not consider additional factors in our empirical analysis.

Mameli et al. (2008) and Paci and Usai (2008) estimate a negative impact of sectoral specialization on local growth. Only Forni and Paba (2002) are able to corroborate the MAR hypothesis. All studies on Italy also find a positive impact of the degree of diversification on local employment growth, thus corroborating Jacobs theory. These findings suggest that, if diversification is always better for growth, regional specialization may hinder economic growth. According to Beaudry and Shiffauerova (2009, pp. 320–321) "this may be first related to the lower flexibility of the specialized regions and consequently to their decreased capacity to adjust to exogenous changes, which may prove critical if the main industry in the region declines." The evidence of a negative effect of specialization can also be interpreted in terms of a product's life cycle: products first develop in a few places (strong specialization) and then diffuse across space (Combes 2000), thus places with a higher specialization in a given sector, display lower (or more negative) growth rates. Finally, Paci and Usai (2008) observe that from the 1990s, the manufacturing industry in Italy has undergone a reorganization process which penalized more highly specialized LLSs.[3]

Besides the degree of specialization and diversification, the two alternative theories (MAR and Jacobs) also relate regional growth performances to the level of local competition, *comp*. According to the MAR theory, "local monopoly is better for growth than local competition, because local monopoly restricts the flow of ideas to others and so allows externalities to be internalized by the innovator" (Glaeser et al. 1992, p. 1127). Porter (1990) supports the Marshallian specialization hypothesis in identifying intra-industry spillovers as the main source of knowledge externalities but suggests that local competition rather than monopoly favors growth in specialized geographically concentrated industries. In line with Porter, Jacobs (1969) also suggests that a more competitive environment is more conductive to innovation and therefore to growth. According to Beaudry and Shiffauerova (2009), only 25 studies attempt to detect the three types of externalities: specialization,

[3]Cingano and Schivardi (2004) observe that the evidence of a negative effect of MAR externalities may be due to the choice of the employment growth as dependent variable. They show that, within the same sample, if the total factor productivity (TFP) growth is used in place of the employment growth as dependent variable, the sign of the MAR coefficient turns out to be positive. TFP measures have also been used in other recent studies on Italy (Cainelli et al. 2013), Spain (De Lucio et al. 2002), and Europe (Dettori et al. 2012). Although it is an unquestionable improvement of the analyses on the effects of agglomeration economies, the choice of productivity measures often creates additional inconvenience for researchers in terms of data availability. Paci and Usai (2008), for example, stated that the use of productivity measures may lead researchers to consider more aggregated geographical levels, with negative consequences in terms of assessment of local externalities (Dekle 2002; De Lucio et al. 2002) and of selection biases (Henderson 2003; Cingano and Schivardi 2004). For these reasons and in consideration of the fact that we are interested in evaluating long-term effects of agglomeration economies, we decided to use employment growth as variable of outcome in our analysis. Census data on employment at LLS level for a large number of sectors, indeed, allow us to consider a time span of about thirty years. Moreover, the use of employment growth also allows us to verify the existence of differences between Manufacturing and Service sectors, whereas studies on TFP only analyze Manufacturing sectors due to the difficulty of measuring TFP levels in service sectors.

diversity, and competition. Porter's view on competition is most often supported in conjunction with Jacobs theory, which is consistent with the Jacobsian model. For the case of Italy, Paci and Usai (2008) find a positive effect of market power (i.e., a negative effect of local competition) on local employment growth. Mameli et al. (2008) find a negative effect of local competition when using 2-digit sectoral level data and a positive effect of local competition when using 3-digit sectoral level data.

Urbanization economies are not only driven by the degree of diversity of an economy but also by the overall density of economic activity, *den*. Ciccone and Hall (1996) argue that an increase in economic density involves the accessibility to a broader supply of local public services and a higher local demand and this may foster local growth. However, a larger size of the local economy also entails congestion effects (higher land prices, higher crime rates, environmental pollution, traffic jams, and excess commuting), so that agglomeration diseconomies may dominate. In other words, regions tend to grow faster if, ceteris paribus, agglomeration economies overcome congestion costs. For the case of Italy, Mameli et al. (2008) report evidence of a positive linear effect of population density, while in Paci and Usai (2008) the effect of population density is positive for the whole sample (including both manufacturing and services) and null for the manufacturing sectors.

Finally, the presence of scale economies means that larger is the size of a plant, *size*, better the possibility to exploit fixed costs. This is the case, for example, in monopolistic competition models. A large size could be source of a more detailed division of labor, promoting specialization and productivity growth. However, a large firm size can lead to an increase in costs, for example, owing to the more difficult and slow information flow or related to managerial incapabilities. Mameli et al. (2008) find a negative effect of scale economies when using data at 2-digit sectoral level (in line with Paci and Usai 2008) and a positive effect of scale economies when using data at 3-digit sectoral level.

6.2.2 Critical Issues

Many empirical studies on local employment growth have used the log-linear model (1), including those on the Italian case (Cainelli and Leoncini 1999; Mameli et al. 2008; Forni and Paba 2002; Paci and Usai 2008). However, we claim that the results of these studies suffer from a number of model mis-specification issues.

First, as mentioned above, all of the previous studies on Italy measure Marshallian externalities, *spe*, with the location quotient (or Balassa index), and in most of the cases, they find a negative effect of specialization on employment growth, notwithstanding the strong anecdotal evidence of the economic success of *industrial districts*, the places where Marshallian externalities are magnified. Indeed, the Marshall's theory on external economies, revisited by Becattini (1979) to explain the successful performance of Italian industrial districts, does not only consider the degree of production specialization to describe the characteristics of industrial districts. The essence of the "industrial atmosphere" does not simply consist of "working on similar things", but it also depends on a number of other factors, such as the prevalence of small- and medium-sized firms often involving family ties, a high degree of mutual trust and tolerance among economic actors, and other socioeconomic factors which contribute to determine the social capital of the region. Additionally, the industrial districts' structures are supported by an infrastructure tailored to the particular needs of the district's industry. In a nutshell, a strong specialization per se might be very dangerous for a region since it may lead higher vulnerability to idiosyncratic shocks, unless other factors (those which contribute to determine the industrial atmosphere) are present in the region generating a sort of risk sharing insurance that protect local firms against these kind of shocks. Thus, in order to capture the effect of Marshallian externalities, a large number of socioeconomic variables should be included in the empirical model. However, this strategy is not always feasible because of the lack of relevant information, especially when, as in our case, the analysis covers a rather long time period. As it will be clarified in Sect. 6.2.3, to solve this problem, we exploit information on the identification of industrial districts in Italy.

Second, most of the previous studies disregard the existence of nonlinearities in the relationship between agglomeration economies and growth. However, nonlinearities are very likely to occur in regional growth.[4] For example, the prevalence of either positive or negative urbanization externalities may depend on the level of economic density (*den*) reached. Thus, one may expect the existence of an inverted U-shaped relationship between local growth and total employment density: below a certain threshold of economic density, positive urbanization externalities overcome congestion costs, while above the threshold, congestion costs prevail. To explore this issue, one may use a semi-parametric framework, where the actual shape of the partial effect can be assessed using smooth functions. Similar arguments can be raised to justify the existence of nonlinearities between growth and industry structure. As for local competition (*comp*), we may expect that, starting from low levels of market power (high levels of competition), an increase of sectoral concentration fosters local economic growth because it allows externalities to be internalized by the innovator (in keeping with the MAR theory), while starting from high levels of local market power, a more competitive environment is more conductive to innovation and, therefore, to growth (in line with Porter and Jacobs). A non-monotonic effect of scale economies (*size*) can also be easily predicted; starting from low plant sizes, a larger plant size may boost economic growth, through a

[4] As a first step in our empirical analysis, we have estimated the log-linear model (1) and obtained results very much in line with previous evidence reported for the case of Italy in studies which used LLS as territorial units of analysis (Paci and Usai 2008; Mameli et al. 2008) (these findings are available upon request). However, the results of a *RESET* test clearly informed us that the log-linear model is mis-specified due to the assumptions on the functional form.

stronger division of labor; above a certain threshold, however, a larger plant size can lead to an increase in information and managerial costs.

Third, most of the previous studies do not control for unobserved spatial heterogeneity when specifying the local economic growth model, disregarding the role of “first nature” characteristics of local areas (Krugman 1993) in affecting their growth performance. The marked unevenness of local development can be partly justified on the basis of space being not uniform: some areas are mainly agricultural systems and are scantly devoted to industrial and service activities; some others are plenty of mountains and are sparsely developed. However, panel-data studies using area fixed effects to capture any sort of localized advantage find that such permanent advantage leave substantial agglomeration effects unexplained.

All in all, in line with Briant et al. (2010), we argue that a number of model mis-specifications may have a much stronger impact on the econometric results than other issues related to the size and the shape of the geographical unit or to the level of sectoral aggregation adopted.

6.2.3 A Semi-parametric Geo-Additive Model

Taking into account all of the above-mentioned remarks, we propose an alternative specification of the empirical local employment growth model:

$$\begin{aligned} y_{r,s,t} = {} & \beta_0 + \theta_1 ID_{r,s} + \theta_2 ID_{r,s'} \\ & + f_1\left(\log(\mathrm{spe}_{r,s,t-\tau})\right) + f_2\left(\log(\mathrm{div}_{r,s,t-\tau})\right) + f_3\left(\log(\mathrm{den}_{r,t-\tau})\right) \\ & + f_4\left(\log(\mathrm{size}_{r,s,t-\tau})\right) + f_5\left(\log(\mathrm{comp}_{r,s,t-\tau})\right) + \gamma_s + \Sigma_t h_t\left(n_r, e_r\right) + \delta_t + \varepsilon_{r,s,t} \end{aligned} \tag{6.2}$$

where f_k and h_t are unknown smooth functions of the covariates[5]; $ID_{r,s}$ is a dummy variable which takes value 1 if the region-sector (r, s) belongs to an industrial district specialized in the same sector (s) and zero otherwise; $ID_{r,s'}$ is a dummy variable which takes value 1 if the region-sector (r,s) belongs to an industrial district specialized in another sector (s') and zero otherwise; θ_1 and θ_2 are their associated parameters; and n and e indicate the latitude (*northing*) and the longitude (*easting*) of the region, respectively. This model provides a relatively flexible framework for the analysis of regional employment growth. First, the inclusion of smooth terms of the covariates allows us to identify non-linearities in the relationship between growth and industry structure without imposing any parametric polynomial form. Second, the inclusion of a geo-additive component (the smooth interaction between latitude and longitude) for each time period permit us to control for time-varying spatial unobserved heterogeneity and, thus, to abstract from heterogeneity of the underlying space. Finally, the inclusion of the dummy

[5]The technique used in this chapter to estimate semi-parametric geoadditive models is widely discussed in Basile et al. (2013).

variables $ID_{r,s}$ and $ID_{r,s'}$ allows us to assess the relative performance of industrial districts, the places where Marshallian externalities occur. Specifically, the two dummies permits us to distinguish between the within-sector and the between-sector *ID* effect. In other words, we suggest that the effect of Marshallian externalities may be simply captured by these dummy variables, while the variable *spe* only captures the vulnerability of the region to idiosyncratic shocks.

6.3 Data and Variables

6.3.1 Data

Following Mameli et al. (2008) and Paci and Usai (2008), the geographical units of observation considered in the present analysis are the LLSs. The number of LLSs in Italy has changed over time. We use the 2001 ISTAT classification which identified 686 LLSs.[6] ISTAT also categorizes LLSs according to whether or not they belong to an industrial district. In particular, it identifies 156 industrial districts in Italy. This piece of information turns out to be of relevance for our analysis, while the degree of urbanization and diversification allows us to put into a test the effect of Jacobs externalities on local labor market performance, the possibility of distinguishing between LLS belonging to an industrial district and other LLSs allows us to assess the role of Marshallian economies on employment dynamics at a very fine territorial level (Table 6.1).

Both manufacturing and service sectors are considered in our analysis. Many empirical studies on the local employment growth focus on the manufacturing sectors (Henderson et al. 1995; Forni and Paba 2002; Cingano and Schivardi 2004). However, modern economies are characterized by an increasing number of service activities that have become an important source of employment. Following the recent literature (Paci and Usai 2008), we take into account this process of structural change in employment dynamics. We consider 15 sectors (subsections of ATECO91-NACE rev. 1 classification; see Table 6.2 in the appendix): ten manufacturing sectors and five service sectors. The public sector is not included. Data on the number of employees and on the number of establishments (local units) in manufacturing and service sectors for the 686 LLS are taken from Italian Census

[6]As it is well known, ISTAT provides data on the number of employees and of establishments in manufacturing and services sectors over the period 1981–2008 by considering two different classifications of LLS, namely the 784 LLSs identified with the 1991s census data and the 686 LLSs identified with 2001s census data. As mentioned above, we use the 2001 classification (686 LLSs) for each decennial census considered in our analysis (1981–1991, 1991–2001, 2001–2008). However, we have also assessed whether the results of our analysis are robust to the choice of the LLS classification. Specifically, we have replicated the regression analysis using data on the 784 LLS (the 1991 criterion) for all the census periods. The results obtained (available upon request) are qualitatively very similar to those reported in the paper.

Table 6.1 Semi-parametric geo-additive model

	Whole economy	Manufacturing	Services
Parametric terms	*Coefficients (s.e. in parentheses)*		
(Intercept)	0.328*** (0.063)	0.468*** (0.097)	0.067 (0.045)
$ID_{r,s}$	1.905*** (0.281)	2.210*** (0.346)	
$ID_{r,s'}$	0.172* (0.092)	0.399** (0.146)	0.195*** (0.067)
Non-parametric terms	*F test and edf (in square brackets)*		
f_1 (log(spe))	229.204*** [3.860]	132.286*** [3.732]	247.476*** [3.893]
f_2 (log(div))	20.962*** [2.481]	39.871*** [1.942]	12.108*** [2.053]
f_3 (log(den))	7.547*** [2.657]	2.167* [1.781]	32.368*** [3.204]
f_4 (log(size))	45.925*** [2.872]	32.663*** [2.896]	19.059*** [2.914]
f_5 (log(comp))	8.115*** [2.872]	6.348*** [2.400]	43.349*** [1.003]
h_{1981} (no, e)	7.190*** [7.190]	8.314*** [6.217]	8.547*** [11.184]
h_{1991} (no, e)	17.292*** [5.472]	11.667*** [5.308]	22.092*** [8.132]
h_{2001} (no, e)	1.851* [6.242]	2.109** [6.715]	9.160*** [11.306]
No. of obs.	27,257	17,006	10,251
$R^2_{\text{adj.}}$	0.094	0.091	0.197
REML	85,784	56,815	23,734

Notes: The dependent variable is the relative employment growth rate: difference between the annual employment growth rate of the s-th sector ($s = 1, , 10$) in the r-th LLS ($r = 1, , 686$) computed for three successive periods (1981–1991, 1991–2001, and 2001–2008) and the annual national employment growth rate of this sector during the same periods. All estimates includes time-fixed effects. Approximated F-tests and associated p-values for the significance of the univariate and the bivariate smooth terms are reported.

of Industries and Services for 1981, 1991, and 2001. These data are obtained through the consultation of the Italian Statistical Atlas of Municipalities (*Atlante Statistico dei Comuni*). Data from the 2008 are taken from the Statistical Register of Active Enterprises (ASIA). Both sources of data are provided by ISTAT. Population and areas data come from ISTAT Population Census.

6.3.2 Variables

As in Combes (2000), each variable used in our empirical analysis is normalized by the value it takes at the national level for the considered sector: this allows us to control for unobserved time-varying sectoral effects. Thus, the dependent variable, $y_{r,s,t}$, is the difference between the annual employment growth rate of the s-th sector ($s = 1, \ldots, 10$) in the r-th LLS ($r = 1, \ldots, 686$) computed for three successive periods (1981–1991, 1991–2001, and 2001–2008) and the annual national employment growth rate of this sector during the same periods:

$$y_{r,s,t} = \log(E_{r,s,t}/E_{r,s,t-\tau}) - \log(E_{s,t}/E_{s,t-\tau}) \tag{6.3}$$

where E stands for employment and t corresponds to the final year of each period (1991, 2001, and 2008), while $t - \tau$ is the initial year of each period (1981, 1991, and 2001).

All explanatory variables refer to the beginning of each period in a way consistent with the idea that agglomeration forces manifest their impact on regional growth after a consistent time lag (Combes 2000). Specifically, we include five explanatory variables capturing the role of (1) specialization, (2) diversification, (3) density, (4) plant size, and (5) local competition. Following the main literature, we measure specialization externalities, $\text{spe}_{r,s}$, by means of the location quotient. This index measures the relative concentration of a sector in an LLS with respect to the average concentration of the same sector in Italy. It can be expressed as follows:

$$\text{spe}_{r,s} = \frac{E_{r,s}/E_r}{E_s/E} \tag{6.4}$$

The r-th LLS is specialized in the s-th sector if the value of $\text{spe}_{r,s}$ is higher than 1, showing that in the LLS considered, the weight of the sector is greater than its weight in the whole country. Values for $\text{spe}_{r,s}$ lower than 1 are evidence of a despecialization. According to the traditional view, a positive effect of $\text{spe}_{r,s}$ would support the MAR theory.

We also try to capture the effect of MAR externalities by directly including the dummy variable $ID_{r,s}$, on the basis of the consideration that Marhsallian economies mainly occur within industrial districts. We also include the dummy $ID_{r,s'}$ to evaluate the impact of industrial district specialized in a given sector s into the employment growth rate of other sectors.

As it is common in the literature, we measure Jacobs or diversification externalities by means of the inverse of the Hirschman–Herfindahl index normalized by the same variable computed at the national level:

$$\text{div}_{r,s} = \frac{1/\sum_{s' \neq s} [E_{r,s'}/(E_r - E_{r,s})]^2}{1/\sum_{s' \neq s} [E_{s'}/(E - E_s)]^2} \tag{6.5}$$

Own-industry employment is excluded because the values of this indicator for the sectors in each LLS differ. A high value of $\text{div}_{r,s}$ means that the r-th LLS has a comparative advantage in a significant share of different sectors (i.e., its production structure is diversified). A low value of $\text{div}_{r,s}$ means that the r-th LLS is specialized in a few industries. Thus, a positive effect of $\text{div}_{r,s}$ would support Jacobs theory.

Total population density, den_r, is used to measure the *scale* of urbanization externalities:

$$\text{dens}_r = \frac{P_r}{A_r} \tag{6.6}$$

where P_r indicates the population in the r-th LLS, and A_r indicates the area in km^2. A positive effect of den_r implies that positive urbanization economies dominate over negative congestion effects.

Following Combes (2000) and O'hUallachain and Satterthwaite (1992), internal economies of scale, $\text{size}_{r,s}$, are measured by the average plant size in the s-th sector located in the r-th LLS compared to Italy as a whole:

$$\text{size}_{r,s} = \frac{E_{r,s}/F_{r,s}}{E_s/F_s} \tag{6.7}$$

where F indicates the number of local units (plants). A positive coefficient associated to $\text{size}_{r,s}$ indicates that the positive effect of a higher division of labor within the firm dominates over the negative effect of higher information and managerial costs.

Following Illy et al. (2011), we measure local competition, $\text{comp}_{r,s}$, using the following normalized Herfindahl index:

$$\text{comp}_{r,s} = \frac{\Sigma_{g=1}^{G}\left(\left(\frac{E_{r,s,g}/F_{r,s,g}}{E_{r,s}}\right)^2 * n_{r,s,g}\right)}{\Sigma_{g=1}^{G}\left(\left(\frac{E_{s,g}/F_{s,g}}{E_s}\right)^2 * n_{s,g}\right)} \tag{6.8}$$

where n is the number of firms, and g indicates the size class of firms in terms of employees. Seven size classes are considered, namely: 1–5, 6–9, 10–19, 20–49, 50–99, 100–499, and more that 500 employees. A negative effect of $\text{comp}_{r,s}$ would support Porter's hypothesis, while a positive effect of $\text{comp}_{r,s}$ would support MAR theory.

6.4 Econometric Results

6.4.1 Evidence from Semi-parametric Models

In this section, we discuss the estimation results of the semi-parametric Model (2), which includes the dummy variables $ID_{r,s}$ and $ID_{r,s'}$ to capture the average within-sector and between-sector "industrial district" effects, smooth univariate terms to identify possible nonlinear effects of agglomeration economies, and the smooth interaction between latitude and longitude to control for unobserved spatial heterogeneity (Table 6.1).

As discussed in the previous session, empirical studies on Italy have reported a negative effect of *spe* both in manufacturing and in services. However, a higher specialization per se does not necessarily mean higher Marshallian economies, while the "industrial district" effect may better identify positive Marshallian externalities.

Indeed, as shown in Table 6.1, the coefficients associated with $ID_{r,s}$ and $ID_{r,s'}$ are always positive and significant, indicating that industrial districts (the places where Marshallian externalities are magnified) perform better, in terms of job creation, than the other LLSs. This is consistent with a huge amount of empirical evidence on the growth success of industrial districts in Italy. However, not surprisingly, the magnitude of the coefficient associated with $ID_{r,s'}$ is much higher in the case of manufacturing than in the case of services.

The middle part of Table 6.1 reports the F-tests for the overall significance of the smooth terms as well as their effective degrees of freedom (*edf*). Each univariate smooth term is specified as a cubic regression spline, while the smooth interaction between *latitude* and *longitude* is specified as a tensor product. F-tests indicate that all terms enter the model significantly. The *edf* is a measure of the term's nonlinearity. If the *edf* is equal to one, a linear relationship cannot be rejected. Evidence reveals that the *edf* is equal to one only for f_5 (log(comp)) in services. The spatial trend term ($h\,(n_r, e_r)$) also is highly significant in all sectors and in all periods, suggesting the presence of an unexplained spatial heterogeneity in local employment growth.

Figures 6.1, 6.2, 6.3, 6.4, and 6.5 portray the smoothed partial effects of univariate terms. The shaded areas highlight the 95 % credibility intervals. The

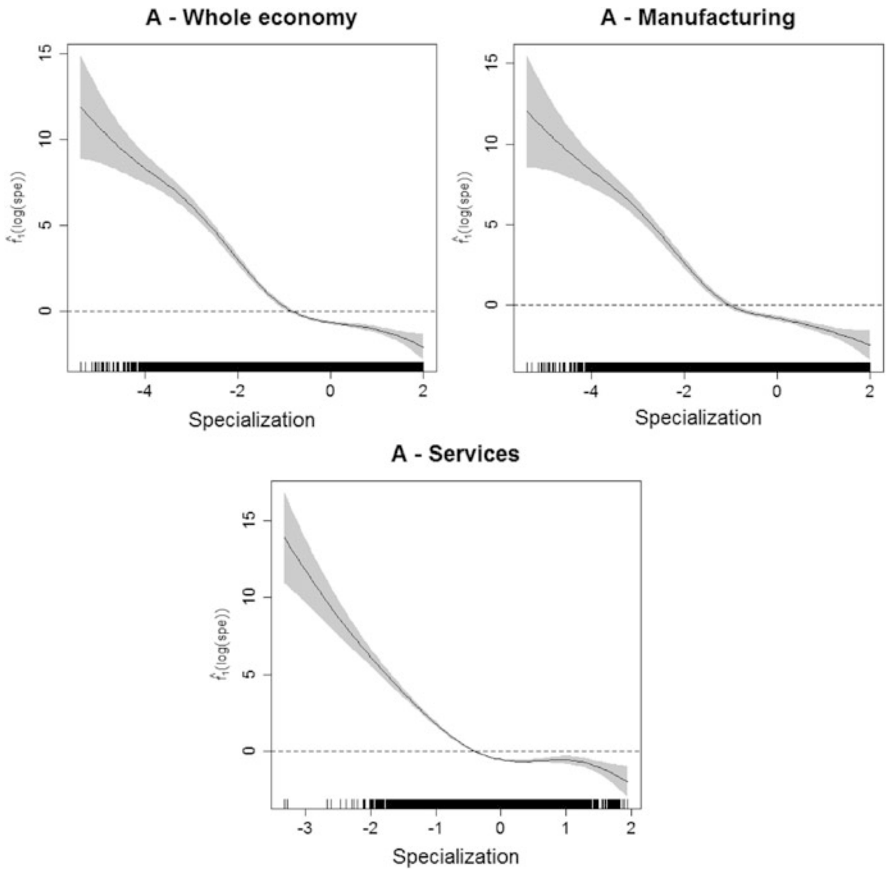

Fig. 6.1 Smooth effect of *spe*

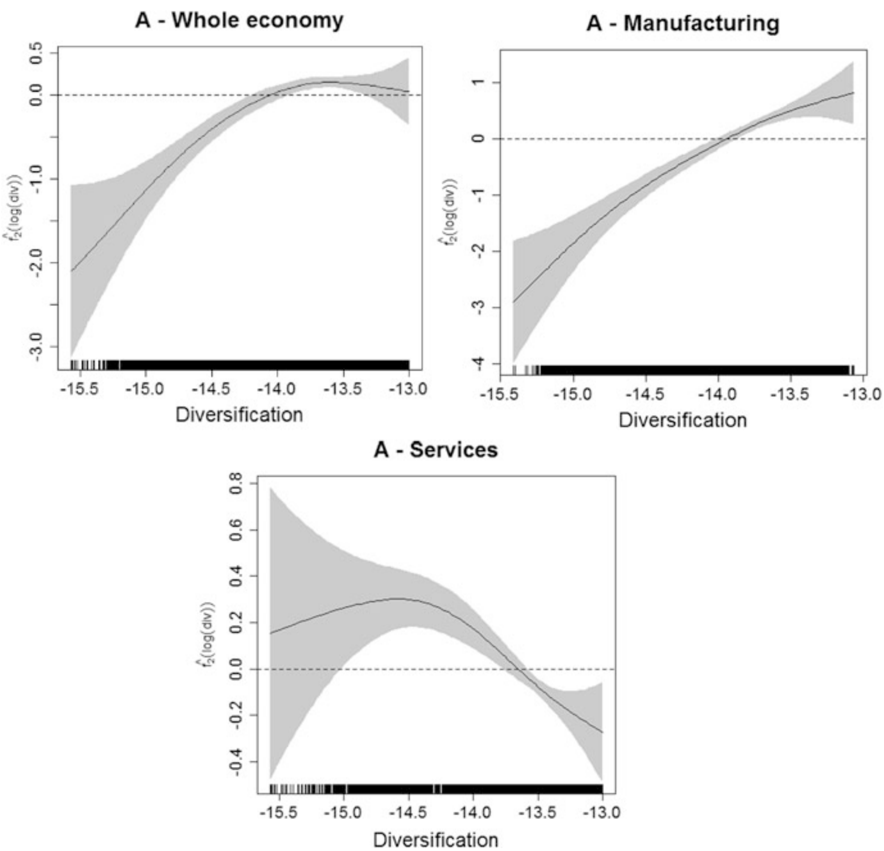

Fig. 6.2 Smooth effect of *div*

log(spe)-plot (Fig. 6.1) confirms that, ceteris paribus, local areas with lower specialization in a sector tend to grow faster in that sector. However, the effect of a decline in specialization always appears to be nonlinear. In particular, we find a hockey stick-shaped relationship between specialization and local employment growth; a higher specialization reduces the employment dynamics due to a higher vulnerability to idiosyncratic shocks, but only up to a certain threshold, after which the relationship between employment growth and *log(spe)* becomes null or negligible.

The effect of diversification is monotonically positive in manufacturing (Fig. 6.2) in line with previous evidence and corroborating Jacobs' theory. For services, it emerges a nonlinear relationship; the effect of diversification on employment growth is null up to a certain threshold, after which it turns to be negative.

Allowing for nonlinearities, we find a hump-shaped relationship between population density, *log*(*den*), and local employment growth (Fig. 6.3); the positive effect of overall population density fades as the density of economic activities reaches some

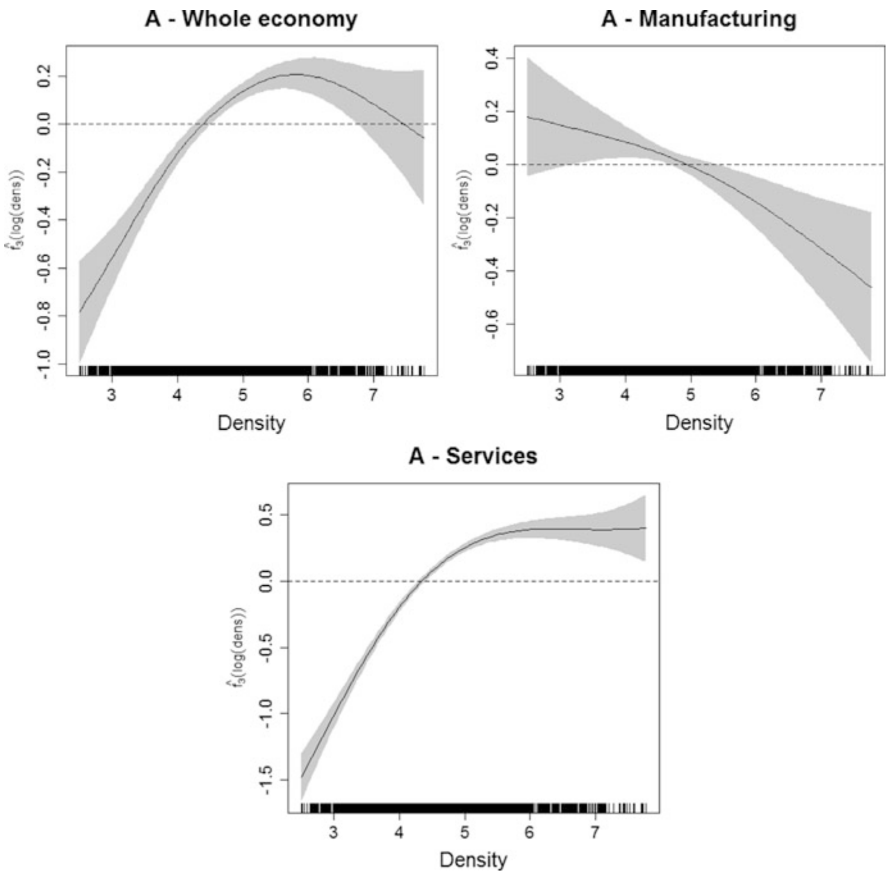

Fig. 6.3 Smooth effect of *den*

threshold value, after which congestion costs overcome agglomeration externalities. This outcome is consistent with the hypothesis that a denser economic activity can exert a positive externality that promotes local growth, but when the level of agglomeration becomes too high, congestion costs kick in and gradually reduce the growth performance. It is worth noticing that in the case of services, the positive treat of the hump-shaped curve prevails over the negative one; the opposite occurs in the case of manufacturing.

We also find evidence of a hump-shaped relationship between employment growth and $log(size)$ (Fig. 6.4); starting from low levels of $log(size)$, an increase in plant size has a positive effect on growth due to, for example, a more detailed division of labor; after a certain threshold (that is starting from high values of $log(size)$), however, an increase in plant size has a negative effect on growth due to an increase in information and managerial costs. The log-linear model masks

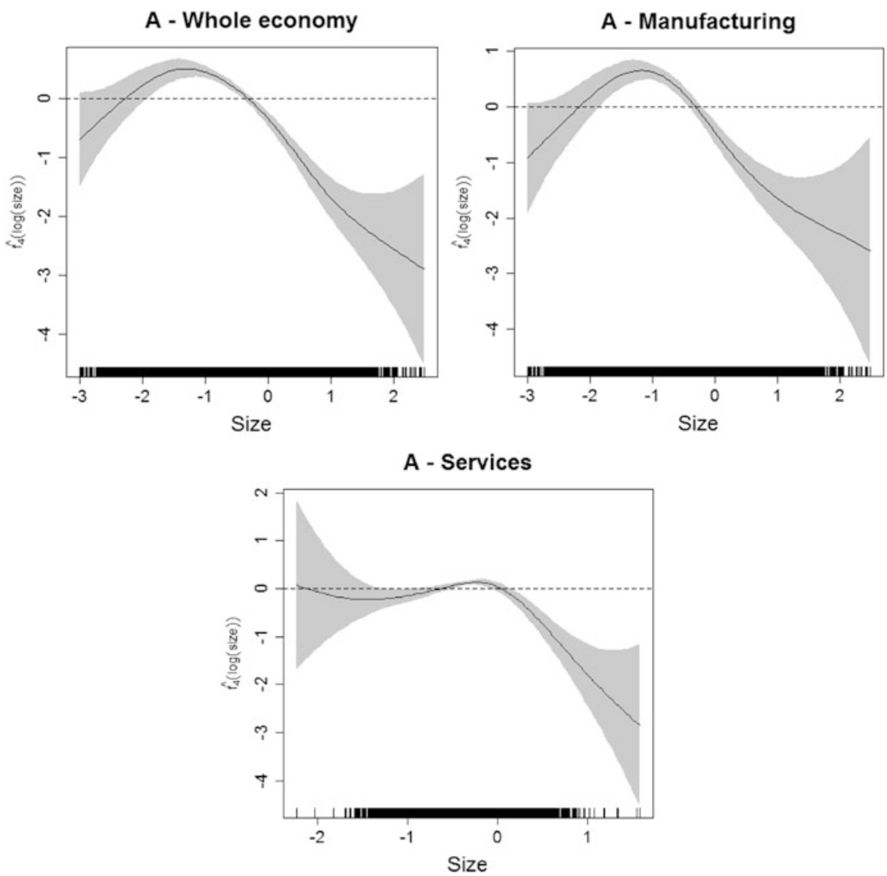

Fig. 6.4 Smooth effect of *size*

these nonlinearities and brings us to conclude for a negative effect of $log(size)$ both in manufacturing and for a null effect of this variable in services.

The relationship between growth and $log(comp)$ (Fig. 6.5) is linear and negative in the case of services, indicating that local competition is always better for growth, in accordance with the Porter's theory. In the case of manufacturing, our semi-parametric estimates provide evidence of a nonlinear relationship between growth and $log(comp)$; starting from low levels of $log(comp)$ (i.e., from high levels of local competition), an increase in market power has a positive effect on growth, corroborating the MAR theory; after a certain threshold (that is starting from high levels of $log(comp)$), a decrease of market power favors local growth. In other words, our results suggest that the validity of Jacobs–Porter hypothesis (according to which local competition is a driving force to urban growth) or of the MAR theory (according to which local competition is an obstacle to urban growth) depends on some cutoff level reached by the degree of local competition.

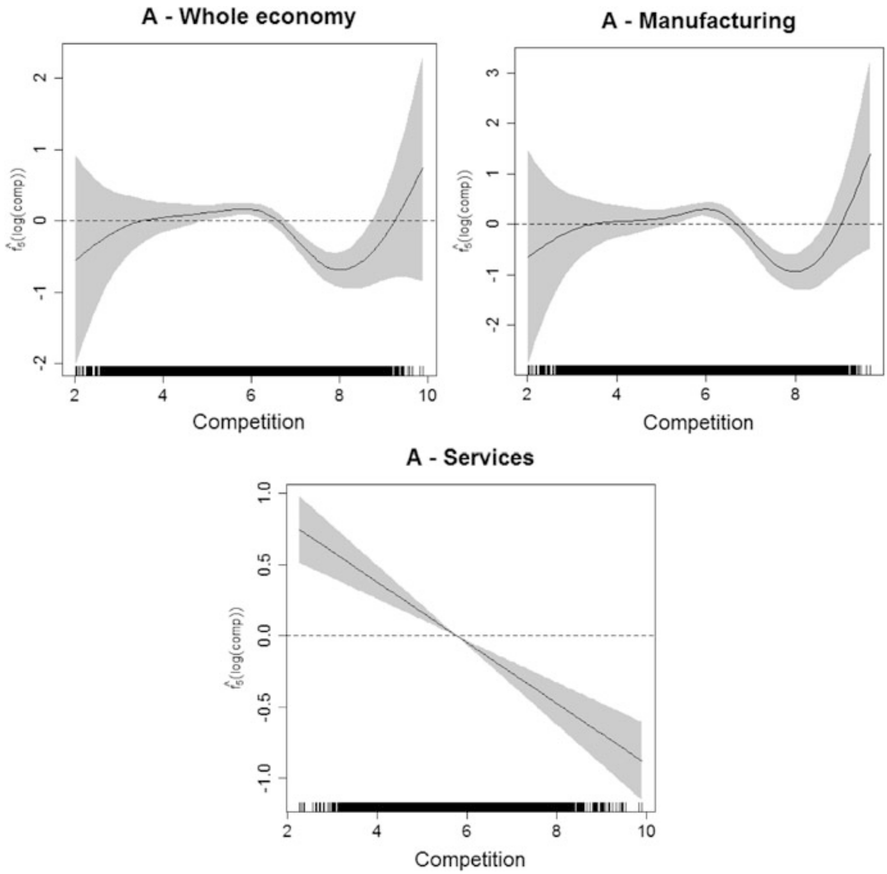

Fig. 6.5 Smooth effect of *comp*

6.5 Conclusions

In this paper, we propose a semi-parametric geo-additive model to analyze the effect of localization and urbanization externalities, local competition, and internal scale economies on sector-region employment growth. This specification allows us to simultaneously address some important issues, such as nonlinearities in the effect of agglomeration externalities and residual spatial heterogeneity. We apply this model to Italy's LLSs data collected for three successive periods (1981–1991, 1991–2001, and 2001–2008).

Moreover, we claim that the variable commonly used to capture the effect of specialization externalities, that is the location quotient, is not suitable to effectively capture Marshallian externalities. Higher specialization levels are indeed an indicator of higher vulnerability to idiosyncratic shocks. In fact, it would be a very hard task to capture Marshallian externalities through a single variable since the essence of the Marshallian externalities depends on a large number of socioeconomic factors. In order to overcome this problem, we exploit the availability of a classification of LLSs in Italy as industrial districts and nonindustrial districts.

Our empirical evidences confirm that industrial districts have performed better than the other LLSs both in manufacturing and service sectors, thus confirming that Marshall externalities exert a positive effect on local employment growth. Moreover, a higher specialization per se has a negative (albeit nonlinear) impact on employment dynamics. A higher diversification, instead, has a positive effect on employment growth in manufacturing sectors corroborating Jacobs theory and a negative effect in services.

The flexibility of the semi-parametric approach also allows us to appreciate that some local characteristics have a nonlinear effect on employment growth. In particular, in keeping with theoretical predictions, the positive effect of urbanization externalities (captured by population density) appears to fade as the density of economic activities reaches some threshold value (in the case of service sectors). Moreover, a hump-shaped relationship between average firm size and local employment growth emerges. Nonlinearities are also evident for the relationship between the level of local competition and employment growth. Besides, a geo-additive model, which incorporates a smooth spatial trend surface, is able to capture residual spatial heterogeneity.

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Appendix

Table 6.2 Sector disaggregation

NACE rev. 1	Sectors
	Manufacturing
DA	Manufacture of food products, beverages, and tobacco
DB	Manufacture of textiles and textile products
DC	Manufacture of leather and leather products
DD	Manufacture of wood and wood products
DE	Manufacture of pulp, paper, and paper products; publishing and printing
DF	Manufacture of coke, refined petroleum products, and nuclear fuel
DG	Manufacture of chemicals, chemical products, and man-made fibers
DH	Manufacture of rubber and plastic products
DI	Manufacture of other nonmetallic mineral products
DJ	Manufacture of basic metals and fabricated metal products
DK	Manufacture of machinery and equipment n.e.c.
DL	Manufacture of electrical and optical equipment
DM	Manufacture of transport equipment
DN	Manufacturing n.e.c.
	Services
G	Wholesale and retail trade; repair of motor vehicles, motorcycles, and personal and household goods
H	Hotels and restaurants
I	Transport, storage, and communication
J	Financial intermediation
K	Real estate, renting, and business activities

Notes: data for the sectors DB, DC, DD, DE, DF, DG, DH, and DI have been merged in pairs. n.e.c. stands for Not Elsewhere Classified

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Chapter 7
Do Agglomeration Externalities Enhance Regional Performances in Production Process? A Stochastic Frontier Approach

Massimiliano Agovino and Agnese Rapposelli

Abstract The aim of the present work is to estimate an aggregate production function for the 20 Italian regions by emphasizing the role that agglomeration externalities (localization externalities and urbanization externalities) and spatial spillovers have in influencing the technical efficiency of the production process. To this purpose, we use the stochastic frontier approach.

The results highlight the relevance and the positive impact that localization and urbanization externalities have in improving the efficiency level of the production process of Northern and Central Italian regions. Furthermore, spatial spillovers represent a source of development and growth for Northern, Central, and Southern regions. In particular, after considering spatial spillovers, we observe a reduction of the concentration and an increase of the diffusion process of efficiency among Italian regions. For some Northern and Central regions, we can observe that there are some richer regions and some poorer regions with regard to their capability to benefit from spatial spillovers.

Keywords Agglomeration externalities • Spatial spillovers • Stochastic frontier • Technical efficiency • Italian regions • Spatial correlation

JEL Classification R10, O1, D24, C2

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7.1 Introduction

In recent years, territory has been seen as an independent production factor able to enter the production function and to affect the efficiency of classic production factors, i.e., labor and capital. With regard to this issue, De Groot et al. state that "The productivity of the open urban economy depends also on spatial factors, internally through density and infrastructure and externally through spatial interaction with other cities and regions. Resources, production factors, and geography then combine with an industrial structure characterized by specialization, competition, and diversity to yield innovation and productivity growth that encourages employment expansion. In the presence of economic diversity and increasing returns, capital and labor are not flowing in opposite directions, as in static neoclassical theory. Instead, the city attracts capital too. Many aspects of this self-reinforcing and virtuous process yield benefits that are external to individual market transactions and such externalities are, therefore, central to agglomeration processes" (De Groot et al. 2007, p. 2).

The principle of agglomeration is mainly associated with the concept of externalities. If these externalities are designed in their positive sense, i.e., in terms of benefits, they can be identified in the so-called agglomeration economies. It is well known that the traditional classification (Hoover 1937; Richardson 1969) divides these agglomeration economies in internal economies, i.e., economies of scale and external economies, i.e., localization economies and urbanization economies. Economies of scale are defined as internal benefits because they are related to the internal organization of the productive activity of firms and they are not caused by factors external to them, such as proximity of other firms or presence of particular services. In contrast, localization and urbanization economies are defined as external benefits or economies. In particular, the former type of economies is derived from benefits external to the individual firm but internal to the sector they belong to, while the latter is derived from benefits external to both the individual firm and to their sector. In short, economies related to the internal production of the firm, that arise from its resources, its internal organizational capacity, and its management efficiency, can be controlled directly by the firm, while external economies depend on production relations that are generated outside of the firm and are not controllable by it. Hence, traditional literature identifies three types of agglomeration externalities: localization externalities, also known as Marshall externalities or MAR (Marshall 1890; Arrow 1962; Romer 1986), "represented by all those advantages the territory can bring to the firm production if it is organized into an agglomeration characterized by localization" (Camatti 2009) and urbanization externalities, also called Jacobs externalities (Jacobs 1969), "represented by all those advantages the territory can bring to the firm production if it is organized into an agglomeration characterized by urbanization" (Camatti 2009). The existence of these two typologies of territorial externalities is one of the key factors of agglomeration, through the action of increasing returns that are generated by interactions and spillovers between firms. Finally, the literature considers Porter externalities (Porter 1990) that are based on the assumption that "the competition among firms at local level represents a source of positive externalities as it encourages the production and the adoption of innovations." (Cingano and Schivardi 2005).

Several empirical studies have tried to determine which is the most important characteristic of the production structure in generating externalities, focusing on the role of sector specialization (localization externalities) and production variety (urbanization externalities) (Cingano and Schivardi 2005). In particular, Glaeser et al. (1992) demonstrate, in their seminal work conducted on a sample of American cities, that localization externalities have a negative effect on growth, while urbanization externalities have a positive effect on it. Subsequent studies extended to other countries (as, for instance, Combes 2000 for the case of France; Bradley and Gans 1998 in Australia; Cainelli and Leoncini 1999; Cingano and Schivardi 2005; Paci and Usai 2001 and Pagnini 2005 in Italy) confirm the negative relationship between productive specialization and growth, while the relationship between urbanization externalities and growth seems ambiguous.

The Italian economy represents a good case study in order to examine the determinants of the dynamics of the production of the regions. Italy, in fact, in the last half century has shown important growth differentials between geographical areas. While in the 1950s and 1960s it has experienced a strong concentration process of population and economic activities in more developed areas of the country, since the 1970s, the peripheral areas have registered a long-run growth higher than other Italian regions thanks to the spread of the specialization and agglomeration pattern typical of industrial districts (Brusco and Paba 1997; Pagnini 2005). In this way, the gradient of Italian development has followed a specific spatial pattern, moving from the North-West of Italy to the North-East and Central Italy, but it has failed to involve significantly Southern regions, which are still characterized by low rates of entrepreneurial activity, by rates of labor force participation lower than that of developed regions, and by high rates of unemployment (Pagnini 2005). In this regard, the present study aims at estimating an aggregate production function for the 20 Italian regions by emphasizing the role that territorial externalities have in influencing the technical efficiency of the production process. In addition, we also consider spatial spillovers among the possible factors that may influence the production process, starting from the reasonable hypothesis that they do not exhaust their effects only within the local economy in which they are generated but they also spread to neighboring regions. More specifically, in this chapter, we want to answer the following question: which is the role of specialization and diversification of regional economic structures? How important is the interdependence (spatial spillovers) between contiguous economic areas? To this end, the stochastic frontier approach seems suitable to explain whether the persistent regional disparity in terms of productivity is due to differences in technology levels, factors endowments, or efficiency (Mastromarco and Woitek 2006).

The chapter is organized as follows. In Sect. 7.2, we define some measures used for agglomeration externalities; in Sect. 7.3, we present the methodology and the data used; in Sect. 7.4, we describe the results obtained, and in Sect. 7.5, we conclude.

7.2 Agglomeration Externalities

Since early empirical studies (Glaeser et al. 1992; Henderson et al. 1995), the focus on the identification of the agglomeration externalities intensity has been developed in terms of some indicators. The empirical literature usually refers to three types of territorial externalities: Marshall, Arrow, Romer (MAR) externalities, Jacobs externalities, and Porter externalities.

MAR externalities are generated through knowledge spillovers between firms within the same industry. In this case, the spatial agglomeration of the industry, and hence its regional specialization, tends to stimulate knowledge spillovers between firms and, therefore, the growth of that local industry (Cainelli and Leoncini 1998). This theory suggests the presence of a monopolistic market: in fact, it allows people to protect their innovations and to make better use of them. These externalities are given by the following indicator:

$$\mathrm{MAR}_{it} = \max_{jt}\left(S_{ijt}/S_{jt}\right)$$

where s_{ijt} denotes the ratio between the number of employed people in sector j in region i at time t and the total number of employed in region i at time t, while s_{jt} denotes the ratio between the number of employed people in sector j at country level at time t and the total number of employed at country level at time t (Duranton and Puga 2000).

Jacobs externalities (Jacobs 1969) are based on the assumption that the industry variety is able to promote the long-term development through cross-fertilization of ideas between different productive activities. Competition is the market form most appropriate to this type of externalities, because only competition allows firms to increase their knowledge levels and thus to survive (Cainelli and Leoncini 1998). Such externalities are commonly expressed by the inverse of the Hirschman–Herfindahl index (Duranton and Puga 2000)[1]:

$$J_{it} = 1\Big/\sum_{j}\left|S_{ijt} - S_{jt}\right|$$

[1]The more the production structure of the corresponding region reflects the national economy diversity, the more the Hefindal index increases (Cirilli and Veneri 2009).

Furthermore,[2] since it is likely that the externalities produced in a specific local economy do not exert their effects only within it but they can affect the performance of other locations (Pagnini 2003), we include an additional variable whose purpose is to quantify the externalities associated with industrial agglomeration processes; therefore, we take into account a variable expressing spillover effects generated by the concentration of employment in the regions close to a given region and whose effect is an improvement of local growth, productivity, and efficiency (Guiso and Schivardi 2007; Battese and Tveteras 2006). We denote this variable with the following expression:

$$\mathrm{WE}_{i,t} = \sum_{k \neq j} E_{k,t} d_{j,k}^{-1}$$

where $E_{k,t}$ represents the number of employed people of location k at time t, $d_{j,k}$ is the distance between two generic regions, and j and k represent the subscripts that identify the element of the distance matrix W. This index is simply a lagged variable in space. In particular, we use as a measure of the distance from one region and others the inverse of the distance expressed in km. This distance matrix has an interesting economic meaning: the increase of distance reduces the strength of ties between a given region and neighboring regions.

7.3 Methodology

Building on the work of Mastromarco and Woitek (2006), we consider a standard growth model with externalities. In particular, we assume a Cobb–Douglas production function where, besides considering production, labor, and the stock of capital (respectively, $Y_{i,t}$, $L_{i,t}$ and $K_{i,t}$), we also include territorial externalities ($\mathrm{MAR}_{i,t}$ and $J_{i,t}$) that, together with technological progress denoted by $A_{i,t}$, represent the Total Factor Productivity level (TFP[3]) (Cingano and Schivardi 2005). This relation is given by $Y_{i,t} = F\left(A_{i,t}, L_{i,t}, K_{i,t}, \mathrm{MAR}_{i,t}, J_{i,t}\right)$.

[2] Porter externalities (Porter 1990), which represent a cross between MAR and Jacobs thesis, are expressed by the following indicator: $P_{ijt} = \left(\mathrm{firm}_{ijt}/s_{ijt}\right) \Big/ \left(\sum_i \sum_j \mathrm{firm}_{ijt} \Big/ \sum_i \sum_j s_{ijt}\right)$, where firm_{ijt} indicates the number of firms in sector j in region i at time t. Due to the unavailability of the number of firms by sector, we are not able to get this indicator and therefore it will be omitted from our analysis.

[3] TFP measures the output growth attributable to technical progress and to efficiency in the combination of production factors.

Assuming that agglomeration externalities and technological progress are external to firms, we model them in the following way:

$$\begin{aligned} Y_{i,t} &= A_{i,t} * \mathrm{MAR}_{i,t}^{\beta_3} * J_{i,t}^{\beta_4} * f\left(L_{i,t}, K_{i,t}\right) \\ \mathrm{TFP}_{i,t} &= A_{i,t} * \mathrm{MAR}_{i,t}^{\beta_3} * J_{i,t}^{\beta_4} \end{aligned} \tag{7.1}$$

Consequently, the function we estimate under spatial spillovers hypothesis is the following one:

$$\begin{aligned} Y_{i,t} &= A_{i,t} * \mathrm{MAR}_{i,t}^{\beta_3} * J_{i,t}^{\beta_4} * \mathrm{WE}_{i,t}^{\beta_5} * f\left(L_{i,t}, K_{i,t}\right) \\ \mathrm{TFP}_{i,t} &= A_{i,t} * \mathrm{MAR}_{i,t}^{\beta_3} * J_{i,t}^{\beta_4} * \mathrm{WE}_{i,t}^{\beta_5} \end{aligned} \tag{7.2}$$

Our analysis will proceed in two steps. First, we consider a model where inefficiency is a function of agglomeration externalities only (Eq. 7.1), and then we implement a model that also includes spatial spillovers among the factors leading to inefficiency (Eq. 7.2). Finally, we compare how the spillover effects affect the determination of efficiency.

We model agglomeration externalities as a spillover effect that increases the productivity of all inputs by increasing efficiency (Hulten and Schwab 1993). Our Cobb–Douglas production function will have the following form:

$$Y_{i,t} = \Lambda_{i,t} * L_{i,t}^{\beta_1} * K_{i,t}^{\beta_2},\ i = 1, \ldots, 20\ ;\ t = 1970, \ldots 1993 \tag{7.3}$$

where $\Lambda_{i,t} = A\tau_{i,t}\omega_{i,t}$, where A denotes the level of technology, $\tau_{i,t}$ is an efficiency measure, with $0 \leq \tau_{i,t} \leq 1$, and $\omega_{i,t}$ is a measurement error.

Writing Eq. (7.3)—*the frontier function*—in logarithms, we obtain:

$$y_{i,t} = \alpha + \beta_1 l_{i,t} + \beta_2 k_{i,t} + \varepsilon_{i,t} + \eta_i + \eta_t,\ i = 1, \ldots, 20\ ;\ t = 1970, \ldots, 1993 \tag{7.4}$$

with $\varepsilon_{i,t} = v_{i,t} - u_{i,t}$
where $u_{i,t} = -\ln\left(\tau_{i,t}\right)$ is a nonnegative random variable and $v_{i,t} = \ln\left(\omega_{i,t}\right)$. In Eq. 7.4, we have also included a time effect η_t that allows for uniform influence of shocks and a set of regional dummies with the aim of capturing the unobserved heterogeneity of regions (η_i). Expected inefficiency—*inefficiency function*—is given by:

$$E\left[u_{i,t}\right] = z_{i,t}\lambda \tag{7.5}$$

where $u_{i,t}$ are assumed to be independently but not identically distributed, $z_{i,t}$ is the vector of variables which influence efficiency, and λ is the vector of coefficients (Mastromarco and Woitek 2006). A single-stage maximum likelihood allows us to estimate both the parameters of the production function and those in Eq. (7.5) (Kumbhakar et al. 1991; Battese and Coelli 1995).

We consider four different specifications for $u_{i,t}$.[4] In the first model, inefficiency is a function of MAR externalities and of Jacobs externalities:

$$E\left[u_{i,t}\right] = \lambda_0 + \lambda_1 \mathrm{MAR}_{i,t} + \lambda_2 J_{i,t} + \eta_i + \eta_t \tag{7.6}$$

The second model also takes into account spatial spillovers:

$$E\left[u_{i,t}\right] = \lambda_0 + \lambda_1 \mathrm{MAR}_{i,t} + \lambda_2 J_{i,t} + \lambda_3 \mathrm{WE}_{i,t} + \eta_i + \eta_t \tag{7.7}$$

The independence assumption of the $u_{i,t}$ is still valid even after the inclusion of the spatial spillovers indicator among the inefficiency factors. In particular, the independence assumption could create problems only if the error term assumes the following form: $u_{i,t} = \lambda \sum_{j=1}^{n} w_{i,j} u_{j,t} + \mu_{i,t}$, where $\lambda \sum_{j=1}^{n} w_{i,j} u_{j,t}$ is the spatial weight matrix, λ is the spatial autocorrelation coefficient, and the $u_{i,t}$ are assumed to be normally distributed independently with zero mean and finite variance (Arbia 2006).[5] In our case, the spatial spillovers indicator enters in the inefficiency function as an exogenous variable not spatially correlated with the error term; consequently, there are no problems related to the spatial autocorrelation of the error term.

The third model takes into account the differences in the reaction of inefficiency dependent on the region (Mastromarco and Woitek 2006). We consider a slope dummy variable $D_{i,t}$, which is equal to one for Northern and Central Italy regions and is equal to zero for Southern regions[6] (Mastromarco and Woitek 2006). This specification allow us to verify whether the impact of externalities is stronger in Northern and Central regions rather than in Southern ones.

$$E\left[u_{i,t}\right] = \lambda_0 + \left(\lambda_{11} + \lambda_{12} D_{i,t}\right) \mathrm{MAR}_{i,t} + \left(\lambda_{21} + \lambda_{22} D_{i,t}\right) J_{i,t} + \eta_i + \eta_t \tag{7.8}$$

$$D_{i,t} = \begin{cases} 1 \text{ if } i = CN \\ 0 \text{ if } i = S \end{cases}$$

[4]Since there are a multitude of regional-specific and time-specific factors that could influence the regions' efficiency, we control for time effect (η_t) and regional dummies (η_i) also in the inefficiency function.

[5]This model is called fixed-effect spatial error model (see Anselin 1998, Chap. 8.).

[6]Northern and Central Italy (NC): Piemonte (PIE), Valle d'Aosta (VDA), Lombardia (LOM), Liguria (LIG), Trentino Alto Adige (TAA), Veneto (VEN), Friuli Venezia Giulia (FVG), Emilia Romagna (EMR), Toscana (TOS), Umbria (UMB), Marche (MAR), Lazio (LAZ). Southern Italy (S): Abruzzo (ABR), Molise (MOL), Puglia (PUG), Campania (CAM), Basilicata (BAS), Calabria (CAL), Sicilia (SIC), Sardegna (SAR).

Finally, the fourth model adds spatial spillovers to the third model (7.8):

$$E\left[u_{i,t}\right] = \lambda_0 + (\lambda_{11} + \lambda_{12} D_{i,t})\,\mathrm{MAR}_{i,t} + (\lambda_{21} + \lambda_{22} D_{i,t})\,J_{i,t} + (\lambda_{31} + \lambda_{32} D_{i.t})\,\mathrm{WE}_{i,t} + \eta_i + \eta_t \tag{7.9}$$

Externalities modeled in this way are interpreted as determinants of inefficiency because they directly explain the inefficiency results of regions.

7.4 Data and Results

The analysis will be conducted on the data of the 20 Italian regions for the period 1970–1993.[7] Data has been obtained from *CRENOS* (*Center for North South Economic Research*).[8] The output measure is regional GDP at constant 1985 prices ($Y_{i,t}$), the capital stock is also expressed at constant 1985 prices ($K_{i,t}$) and, the measure for labor input is the number of employed people ($L_{i,t}$). Moreover, since the number of employees in different production sectors is useful for computing the indexes that express territorial externalities ($\mathrm{MAR}_{i,t}$ and $J_{i,t}$), we also consider:

- the employees in five manufacturing sectors: minerals and nonmetallic mineral products; metal products and machinery and transport equipment; food, beverages, and tobacco; textiles and clothing, leather, and footwear; paper and printing products; wood, rubber, and other industrial products. In particular, we consider only these five sectors because data for other manufacturing sectors are not available;
- the employees in four service sectors: trade, hotels, and public establishment; transport and communication services; credit and insurance institutions; and other market services;
- the employees in the construction sector;
- the employees in the fuel and power products sector;
- the employees in mining and chemical sectors.

All variables are expressed in logarithms.

Table 7.1 reports the statistical summary of the logarithm of the variables. We show the variance decomposition in two components: the between or interregional variability that embodies the permanent differences among regions and the within or intra-regional variability that relies on time observations by country and that considers the position of each region at each date compared to his average over the whole period. We may note that the between variability is higher than the within variability for all variables considered. In particular, we may note that the range

[7]The observation period is restricted to the years 1970–1993 because at the moment, more recent data are not available.

[8]Regio-IT1970-2004 and Regio(cap)-IT_70-94 (www.crenos.it).

Table 7.1 Statistical summary

Variable		Mean	Std. Dev.	Min	Max	Observations
GDP ($Y_{i,t}$)	Overall	10.04341	1.1109	7.3804	12.1599	$N = 480$
	Between		1.1224	7.5797	11.9080	$n = 20$
	Within		0.1865	9.6031	10.3773	$T = 24$
Capital ($K_{i,t}$)	Overall	11.9989	0.9735	9.5124	14.0232	$N = 480$
	Between		0.9623	9.8894	13.6795	$n = 20$
	Within		0.2570	11.3282	12.5375	$T = 24$
Labor ($L_{i,t}$)	Overall	6.5820	1.0297	3.9627	8.30825	$N = 480$
	Between		1.0533	4.0413	8.2473	$n = 20$
	Within		0.0627	6.4052	6.7208	$T = 24$
MAR	Overall	0.3658	0.2525	0.0267	1.0649	$N = 480$
	Between		0.2484	0.0720	0.8878	$n = 20$
	Within		0.0706	0.1153	0.6432	$T = 24$
J	Overall	1.7220	0.5528	0.4961	3.3571	$N = 480$
	Between		0.5159	0.9124	2.8145	$n = 20$
	Within		0.2284	0.9525	2.4151	$T = 24$
WE	Overall	7.02893	0.1530	6.6568	7.4044	$N = 480$
	Between		0.1460	6.7551	7.3453	$n = 20$
	Within		0.0557	6.9160	7.1151	$T = 24$

MAR Marshall, Arrow, Romer externalities, *J* Jacob externalities, *WE* spatial spillovers

of variation of specialization externalities (MAR) is quite large (about one, with a minimum value which tends to zero and a maximum value slightly greater than one); this highlights the presence of regions characterized by low level of specialization that are opposed to regions that are highly specialized. The range of variation of the diversification externalities (J) is almost three times the range of specialization externalities (2.8, with a minimum value of 0.5 and a maximum value slightly higher than 3), and even here we observe two opposite situations: regions characterized by little diversification and regions that are very diversified. Finally, the variable measuring spatial spillovers (WE) presents a much smaller range of variation (0.7, with a minimum of 6.6 and a maximum of about 7.5); this highlights a minor difference, in terms of spillover, between the Italian regions and that the spillover effect has a wide spread and it is independent from the regional specialization and diversification.

In Table 7.2, we report the estimates results of the models considered.[9] The Likelihood ratio test, rejecting the null hypothesis in all four cases, confirms the presence of technical inefficiency [for critical values of the test, see Kodde and Palm

[9]We implement the same analysis controlling for a country-specific deterministic trend; in particular, we define a td_i variable, where t is a polynomial in time and d_i is a regional dummy. The results are similar to those reported in Table 7.1. For space reasons, we do not show them; interested readers can request them to the authors.

Table 7.2 Results

	Variables	Basic model Without spatial spillovers (1)	 With spatial spillovers (2)	Regional model Without spatial spillovers (3)	 With spatial spillovers (4)
Frontier function	Constant	0.1675*	0.4540***	0.0253	0.4497***
		(1.7499)	(4.3512)	(0.3315)	(6.1125)
	Capital	0.5329***	0.4585***	0.5539***	0.4595***
		(35.2112)	(25.4018)	(46.9051)	(35.6903)
	Labor	0.5534***	0.6454***	0.5341***	0.6387***
		(39.0471)	(34.1017)	(49.1599)	(47.2472)
	Time effect	Yes	Yes	Yes	Yes
	Regional dummies	Yes	Yes	Yes	Yes
Inefficiency function	Constant	−0.1061**	3.1456***	0.2720***	2.3795***
		(−2.4448)	(11.7304)	(6.4980)	(10.3614)
	MAR	0.4660***	0.3675***	0.0784**	−0.0086
		(13.0338)	(8.5651)	(2.2987)	(−0.2122)
	J	0.0470**	0.0597***	−0.0379**	−0.1016***
		(2.9873)	(3.6942)	(−2.1069)	(−4.7308)
	WE		−0.4606***		−0.2867***
			(−11.5209)		(−8.3364)
	D × MAR			−0.4426***	−0.2713***
				(−6.8938)	(−4.1569)

	D × J			−0.0429***	0.0706***
				(−4.9071)	(2.7527)
	D × WE				−0.0261***
					(−2.7709)
	Time effect	Yes	Yes	Yes	Yes
	Regional dummies	Yes	Yes	Yes	Yes
	σ^2	0.0082***	0.0057***	0.0045***	0.0031***
		(10.0389)	(10.1064)	(10.5232)	(17.5473)
	$\gamma = \frac{\sigma_u^2}{\sigma_v^2 + \sigma_u^2}$	0.8662***	0.7202***	0.7421***	0.1252***
		(20.3906)	(9.1487)	(10.4378)	(8.6684)
	LR test of $\sigma_u^2 = 0$	371.2250***	503.1071***	642.0008***	711.4107***
	Log-likelihood	541.7245	607.6656	677.1125	711.8174
	Mean efficiency	0.8553	0.8562	0.8706	0.8874

Values in parenthesis denote t statistics
MAR denotes Marshall, Arrow, Romer externalities, *J* denotes Jacob externalities, *WE* denotes spatial spillovers
**, **, *: 1 %, 5 %, 10 %, respectively

(1986)]. In addition, the significance of the parameter γ, i.e., the ratio between the variance of the inefficiency term σ_u^2 and the sum of the total variance $\sigma_v^2 + \sigma_u^2 = \sigma^2$, shows that 86 % (column 1), 72 % (column 2), 74 % (column 3), and 12.5 % (column 4) of the output change among Italian regions is due to differences in their technical inefficiencies.

Log Likelihood values, being higher, always lead to prefer the model with spatial spillovers to the one without them.

With regard to the first model, all parameters of the production function are significant and have the correct sign. In particular, the elasticity of capital is equal to 0.53, while labor elasticity is equal to 0.55 (column 1). The effects of MAR and Jacobs externalities have a negative effect on efficiency, leading to a reduction. With regard to MAR externalities, the negative effect of specialization on efficiency could be explained by the fact that a high specialization generates low flexibility and poor adaptability of products, technologies, and infrastructure when the sector is in decline; on the contrary, more flexible sectors would be more able to convert their operations (Combes 2000). The negative effect of specialization on the efficiency refers to industrial and services sectors (see footnotes 6 and 7) (Combes 2000). Jacobs externalities, with their positive sign, show that a higher level of production diversification makes regions less efficient. Combes (2000) observes a positive relationship with urbanization economies only for the high-tech industrial sector, while he verifies a negative relationship for traditional industrial sectors. The negative impact of Jacobs externalities on the efficiency of the production process is supported both by the work of Henderson (1997) and Combes (2000), who found the presence of urbanization economies only for new industries, not for the nature ones.

By examining column (2), we can note that MAR and Jacobs externalities, as well as being significant, still retain their negative impact on efficiency. On the contrary, the coefficient associated with spatial spillovers, as well as being significant, has a negative sign thus showing its positive effect on efficiency. It is evident that the externalities associated with industrial agglomeration through spillover effects generated by the concentration of employed people in the regions close to a given region have a positive effect on the production process of that region. In our case, given the positive impact of spatial spillovers on efficiency, we look at what is called "concentrated development" that is expected when regions get a positive benefit from external growth opportunities (Capello 2009).

With the introduction of regional effects in the other two specifications of the model (columns 3 and 4), the reading of the results becomes more complicated. For this reason, we introduce a different way of interpreting these results, as suggested by Mastromarco and Woitek (2006):

$$d\tau = -\tau\lambda_i \frac{dz_i}{z_i} \tag{7.10}$$

Table 7.3 Efficiency change compared to percentage change in externalities

Externalities	Italy (basic model)		NC (regional model)		S (regional model)	
	(1)	(2)	(3)	(4)	(3)	(4)
MAR	−4 %	−3 %	3 %	2.4 %	−0.7 %	Not significant
J	−0.4 %	−0.5 %	0.7 %	0.3 %	−0.3 %	0.9 %
WE		4 %		2.8 %		2.5 %

MAR Marshall, Arrow, Romer externalities, *J* Jacob externalities, *WE* spatial spillovers

Hence, we can express the results as change in efficiency due to a percentage change in externalities. For example, by calculating Eq. (7.10) in terms of mean efficiency (equal to 0.8553, column 1 in Table 7.2), we obtain that a 10 % increase in MAR and Jacobs externalities leads to an efficiency change equal to −4 % (MAR) and −0.4 % (Jacobs). This highlights the negative impact of both externalities and the higher impact of MAR externalities compared with Jacobs externalities.

In Table 7.3, we report the results of Eq. (7.10) for the different estimates proposed. By observing column 2, in addition to verifying the continuing negative impact of MAR and Jacobs externalities on efficiency, we may note that spatial spillovers have a positive effect, equal to 4 %, on efficiency.

By focusing on regional analysis, we observe that in the case without spatial spillovers, the differences between the two areas of the country are substantial (column 3). In particular, we verify that the productive efficiency of Central and Northern Italy is positively influenced by both specialization and urbanization externalities (Paci and Usai 2001; Henderson et al. 1995). We find an opposite situation for Southern Italy, where the effect of both externalities results to be negative. The only thing that unites the two Italian areas is given by the minor weight of Jacobs externalities compared to MAR externalities. Finally, in the fourth model (column 4), we observe that MAR externalities have no effect on Southern regions, whereas Jacobs externalities register a positive impact on efficiency. It is worth stressing that spatial spillovers produce a positive impact on both areas of the country, more pronounced in Central and Northern Italy than in Southern Italy (2.8 % vs. 2.5 %).

Two main findings arise from these estimates results: first of all, the dynamics of regional production are highly interdependent (spatial spillovers are significant and positive); second, their link intensity grows as the distance among regions is reduced. In particular, regions surrounded by neighbors with a high propensity to growth tend to have a greater development, all other things being equal. The opposite effect is obtained for regions surrounded by neighbors with a low propensity to growth. These findings open new directions for future research, particularly in the investigation of the sources of spillovers between geographical regions. Their existence also raises a question about the design and the scope for policies to stimulate development at the local level. In particular, policies with the aim of encouraging local development should consider the externalities that may occur between neighboring areas as a result of their actions, and if they turn out to be positive, the competent authorities should facilitate their dissemination. In this case, due to spillover effects, it would develop a "domino effect" that would involve not only the region where local development policy has been implemented, but it would also positively affect the neighboring regions.

7.4.1 Importance of Spatial Spillovers on Regions' Efficiency

In this section, we want to answer the following question: how important are spatial spillovers in determining the efficiency of individual regions? In this regard, we report in Table 7.4, the efficiency ranking for each region by considering the results arising from the assumptions on the $u_{i,t}$ term (presence and absence of spatial spillovers) in Eqs. (7.6) and (7.7).

The efficiency ranking analysis for the year 1993 highlights the presence of three groups of regions. The first group consists of the regions that show the same position in the rankings in all models considered: Piemonte, Emilia Romagna, Veneto, Friuli Venezia Giulia, Liguria, Marche, Calabria, and Sicilia [indicated by (*)]. The second

Table 7.4 Efficiency scores and efficiency ranking, 1993

Macro area	Regions	Without spatial spillovers		With spatial spillovers	
		Efficiency score	Efficiency ranking	Efficiency score	Efficiency ranking
North-West of Italy	PIE (×)	0.9356	7	0.9382	9
North-West of Italy	VDA (+)	0.8803	12	0.9714	3
North-West of Italy	LOM (−)	0.924	9	0.9078	12
North-East of Italy	TAA (+)	0.8956	11	0.9418	8
North-East of Italy	VEN (×)	0.9191	10	0.9148	10
North-East of Italy	FVG (×)	0.9737	2	0.9791	2
North-West of Italy	LIG (×)	0.9868	1	0.9891	1
North-East of Italy	EMR (×)	0.9627	3	0.9626	4
Central Italy	TOS (−)	0.9509	5	0.9467	7
Central Italy	UMB (+)	0.9455	6	0.9581	6
Central Italy	MAR (×)	0.9583	4	0.9587	5
Central Italy	LAZ (−)	0.9306	8	0.9145	11
South Italy	ABR (+)	0.8778	13	0.8912	13
South Italy	MOL (+)	0.7597	18	0.8054	16
South Italy	CAM (−)	0.7664	17	0.7581	19
South Italy	PUG (−)	0.8279	15	0.8173	15
South Italy	BAS (+)	0.7181	19	0.7616	18
South Italy	CAL (+)	0.6929	20	0.7111	20
South Italy	SIC (×)	0.7709	16	0.7788	17
South Italy	SAR (+)	0.829	14	0.8621	14

(−), (+), (×): first, second, and third group, respectively

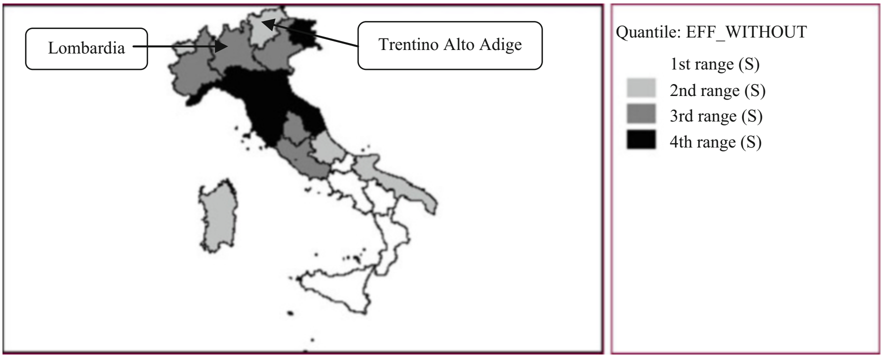

Fig. 7.1 Efficiency scores without spatial spillovers, year 1993

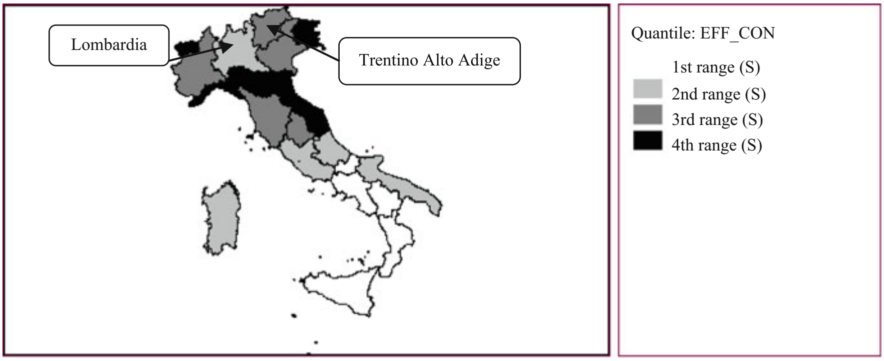

Fig. 7.2 Efficiency scores with spatial spillovers, year 1993

group consists of the regions which benefit from the positive effects of spatial spillovers, thus improving their rankings and their efficiency scores: Valle d'Aosta, Trentino Alto Adige, Abruzzo, Umbria, Molise, Basilicata, Sardegna, and Calabria [indicated by (+)]. The third group includes regions located at the bottom of the ranking as they suffer a loss of efficiency due to the presence of spatial spillovers: Lombardia, Toscana, Lazio, Campania, and Puglia [indicated by (−)].These results are very important because they reveal substantial differences among Italian regions due to the presence of spatial spillovers. In particular, their effects are not obvious; in fact, some regions benefit from their presence, while others are indifferent or suffer from a negative effect in terms of efficiency.

By observing Figs. 7.1 and 7.2, we can note that spatial spillovers affect the results in terms of efficiency. In particular, after considering spatial spillovers, we observe a reduction of the concentration and an increase of the diffusion process of efficiency among Italian regions. Hence, for some Northern and Central regions we can observe that there are some richer regions and some poorer regions with regard to their capability to benefit from spatial spillovers, which represents a nondiscretionary input.[10] More specifically, richer regions lose efficiency, while poorer regions gain in efficiency from the first ones.

The concepts of richer and poorer regions find their justification in our results, which are also in line with Pagnini's findings (2005). In particular, Pagnini (2005) concludes that the geographical spread of growth has strong elements of geographical viscosity. Based on this result, it is interesting to check whether, for example, at the origin of industrial takeoff of some Central and North-East regions it is their geographical proximity to the North-West regions, which still in the 1960s showed in some areas high rates of employment growth. In the next two decades, the North-West regions would begin to show signs of a slowdown for the effect of congestion costs due to the high employment density, and this could largely explain the loss of efficiency of these regions. Central and North-East areas, however, would carry in their growth thanks to the self-propelling push which derived from the spillovers generated between groups of neighboring regions characterized by high growth.

For example, we can see how Lombardia changes from a dark gray in Fig. 7.1 (a more efficient region in the model without spatial spillover) to a light gray in Fig. 7.2 (a less efficient region in the model with spatial spillover): in this case, we can identify this region as a richer one. On the contrary, Trentino Alto Adige changes from a light gray in Fig. 7.1 (a less efficient region in the model without spatial spillover) to a dark gray in Fig. 7.2 (a more efficient region in the model with spatial spillover): in this case, we can identify this region as a poorer region. This result is justified by the fact that Lombardia (a richer region) mostly borders on North-East regions (Veneto, Trentino Alto Adige, and Emilia Romagna) that turn out to be, considering Pagnini (2005) hypothesis, poorer regions; these regions would exploit the ability to produce spillover of Lombardia, thereby improving their production capacity. The presence of growing congestion costs in the North-West of Italy and the proximity of regions unable to develop spillovers could have reduced the productive efficiency of Lombardia. We do not obtain the same result for Piemonte, which mostly borders on North-West regions; in this case, Piemonte could not have suffered a loss of efficiency in its production process because the growth of congestion costs could have been partly damped by the proximity of regions able to develop spillovers.

7.4.2 The Capability to Benefit from Spatial Spillovers for Italian Regions: A Spatial Confirmatory Analysis

We conclude our analysis by investigating the capability to benefit from spatial spillovers for "richer" and "poorer" regions. More specifically, we first implement

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[10]Nondiscretionary variables are variables on which the operating unit does not have control, such as weather conditions, soil characteristics, and firm topography (Maietta 2007).

Moran's scatterplot[11] of regions' efficiency scores, and then we present the results of local Moran's test. Specifically, Moran's I coefficient is defined as follows:

$$I = \frac{\sum_i \sum_j W_{ij} \left(X_i - \mu\right) \left(X_j - \mu\right)}{\sum_j \left(X_j - \mu\right)^2},$$

where X_i and X_j indicate the variables describing the phenomenon under investigation observed in region i and in region j, respectively, μ is the average value in the sample, and W_{ij} is the standardized matrix of spatial contiguity, which specifies the criteria for defining contiguity; in this case, we use a matrix of inverse distances, expressed in kilometers, between one region and another. This index allows us to establish the relationship existing between a phenomenon observed in a given region j and the same phenomenon observed in contiguous regions. Moran's scatterplot (Fig. 7.3) shows the Moran's I coefficient as the slope of the regression line in the scatterplot, where the spatial lag of the annual average efficiency scores is on the vertical axis (respectively, W_M_WITHOUT for the model without spatial spillovers and W_M_WITH for the model with spatial spillovers) and the annual average efficiency scores is on the horizontal axis (respectively, M_WITHOUT for the model without spatial spillovers and M_WITH for the model with spatial spillovers) (both variables standardized). Figure 7.3 shows a high positive value of the Moran's I coefficient (respectively, 0.6987 for model without spatial spillovers and 0.6642 for model with spatial spillovers),[12] which indicates positive spatial correlation for the annual average efficiency scores.[13] This result highlights the existence of a spatial relationship among Italian regions in terms of production process efficiency scores. In particular, it is evident the existence of a strong spatial spillover between contiguous regions, which continues even after controlling for spillover effects and that drives the capability to benefit from spatial spillovers.

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[11]The Moran's scatterplot provides a tool for visual exploration of spatial autocorrelation (Anselin 1996, 2002). The four different quadrants of the scatterplot identify four types of local spatial association between a region and its neighbors: (HH) a region with high efficiency score surrounded by neighbors with high efficiency score (quadrant I); (LH) a region with low efficiency score surrounded by neighbors with high efficiency score (quadrant II); (LL) a region with low efficiency score surrounded by neighbors with low efficiency score (quadrant III); and (HL) a region with high efficiency score surrounded by neighbors with low efficiency score (quadrant IV). Quadrants I and III pertain to positive forms of spatial dependence, while quadrants II and IV represent negative spatial dependence (Rey and Montuori 1999).

[12]The null hypothesis of Moran's I test is spatial independence. According to our results, we reject the null hypothesis at the 1 % level, and we conclude that the annual average of the regions' efficiency scores presents spatial autocorrelation.

[13]Moran's I test, implemented on efficiency scores for each year of the analysis, always rejects the null hypothesis of spatial independence. For reasons of space, we do not show these results, but interested readers can request them to authors.

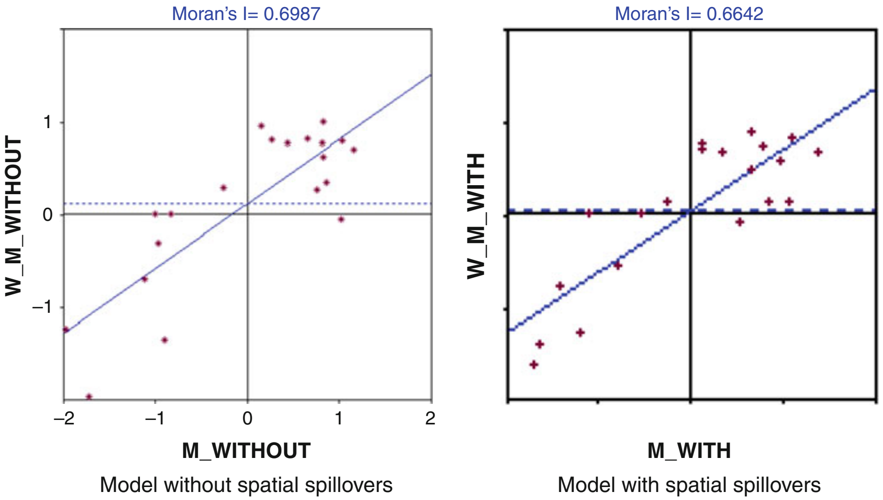

Fig. 7.3 Moran's scatterplot of regions' annual average efficiency scores—model without and with spatial spillovers

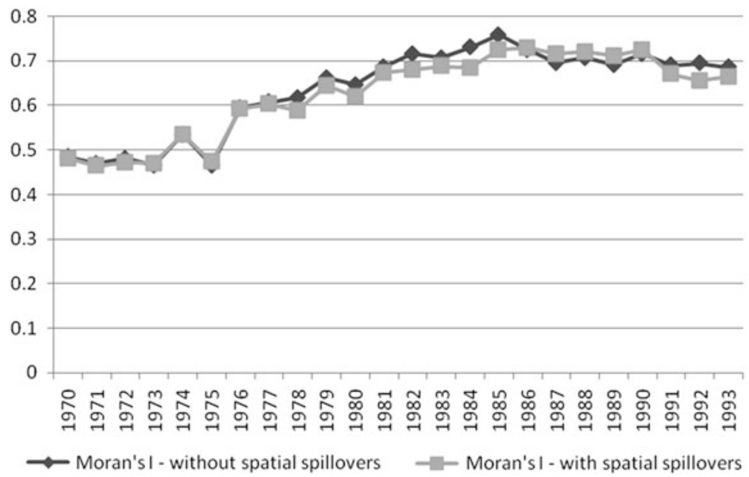

Fig. 7.4 Moran's I of annual efficiency scores—model without and with spatial spillovers

Figure 7.4 shows how Moran's Index for annual efficiency scores calculated for both models continues to overlap during the whole period of analysis; this also highlights the presence of a spatiotemporal persistence in the efficiency scores of the production process of the Italian regions even after checking for spillover effects.

Table 7.5 Local measures of spatial association: efficiency scores—model without spatial spillovers

Macro area	Regions	$p < 0.05$	Q1	Q2	Q3	Q4
North-West of Italy	PIE	11	11	0	0	0
North-West of Italy	VDA	0	0	0	0	0
North-West of Italy	LOM	1	1	0	0	0
North-East of Italy	TAA	0	0	0	0	0
North-East of Italy	VEN	0	0	0	0	0
North-East of Italy	FVG	0	0	0	0	0
North-West of Italy	LIG	13	13	0	0	0
North-East of Italy	EMR	24	24	0	0	0
Central Italy	TOS	24	24	0	0	0
Central Italy	UMB	0	0	0	0	0
Central Italy	MAR	10	10	0	0	0
Central Italy	LAZ	0	0	0	0	0
South Italy	ABR	0	0	0	0	0
South Italy	MOL	0	0	0	0	0
South Italy	CAM	17	0	0	17	0
South Italy	PUG	17	0	0	17	0
South Italy	BAS	24	0	0	24	0
South Italy	CAL	24	0	0	24	0
South Italy	SIC	18	0	0	18	0
South Italy	SAR	0	0	0	0	0

$p < 0.05$ Number of years local statistic is significant at 0.05, Q1—Number of years local statistic is in quadrant 1 of Moran's scatterplot, Q2—Number of years local statistic is in quadrant 2 of Moran's scatterplot, Q3—Number of years local statistic is in quadrant 3 of Moran's scatterplot, Q4—Number of years local statistic is in quadrant 4 of Moran's scatterplot

The capability to benefit from spatial spillovers is guaranteed by the stability of spatial clusters during the period analyzed. In particular, this effect is evident from the results of local Moran's test (Anselin 1996), which allows to identify the presence of spatial clusters (see Tables 7.5 and 7.6).

The local Moran's test (Anselin 1996) can be used to identify local clusters (regions where adjacent areas have similar values) or spatial outliers (areas distinct from their neighbors). In particular, the Local Moran statistic decomposes Moran's I into contributions for each location, I_i. The sum of I_i for all observations is proportional to Moran's I, an indicator of global pattern. Thus, there can be two interpretations of Local Moran statistics, one as indicators of local spatial clusters and the other as a diagnostic for outliers in global spatial patterns. In Tables 7.5 and 7.6, we report the results from the application of the Local Moran statistics to the efficiency scores in each years, both for models without and with spatial spillovers (in the third column we indicate the number of years for which the local statistic provides indications of clustering using a pseudo-significance level of $p = 0.05$, while in columns 4–7, we indicate the number of years for which the statistic is

Table 7.6 Local measures of spatial association: efficiency scores—model with spatial spillovers

Macro area	Regions	$p < 0.05$	Q1	Q2	Q3	Q4
North-West of Italy	PIE	11	11	0	0	0
North-West of Italy	VDA	2	2	0	0	0
North-West of Italy	LOM	0	0	0	0	0
North-East of Italy	TAA	0	0	0	0	0
North-East of Italy	VEN	0	0	0	0	0
North-East of Italy	FVG	0	0	0	0	0
North-West of Italy	LIG	21	21	0	0	0
North-East of Italy	EMR	21	21	0	0	0
Central Italy	TOS	13	13	0	0	0
Central Italy	UMB	0	0	0	0	0
Central Italy	MAR	0	0	0	0	0
Central Italy	LAZ	0	0	0	0	0
South Italy	ABR	0	0	0	0	0
South Italy	MOL	1	0	0	1	0
South Italy	CAM	24	0	0	24	0
South Italy	PUG	24	0	0	24	0
South Italy	BAS	24	0	0	24	0
South Italy	CAL	24	0	0	24	0
South Italy	SIC	19	0	0	19	0
South Italy	SAR	0	0	0	0	0

$p < 0.05$ Number of years local statistic is significant at 0.05, Q1—Number of years local statistic is in quadrant 1 of Moran's scatterplot, Q2—Number of years local statistic is in quadrant 2 of Moran's scatterplot, Q3—Number of years local statistic is in quadrant 3 of Moran's scatterplot, Q4—Number of years local statistic is in quadrant 4 of Moran's scatterplot

significant in each of the four quadrant of the Moran's scatterplot). This results show for both models that:

– 100 % of local indicators that are significant are situated in either quadrants I and III of the Moran's scatterplot, reflecting HH and LL clustering respectively;
– two strong regional clusters emerge and seem to be rather persistent in the period analyzed. The first one is Northern-Central Italy cluster, which includes high efficiency scores regions such as Piemonte, Liguria, Emilia Romagna, and Toscana, each of which appears in quadrant I when its local Moran is significant. The second one is Southern Italy cluster; it consists of low efficiency scores regions such as Campania, Puglia, Basilicata, Calabria, and Sicilia, each of which appears in quadrant III when its local Moran is significant. The spatiotemporal stability of the clusters allows the continuous and not occasional contact between the regions, and this allows the capability to benefit from spatial spillovers.

These results show a persistent dualism on the regions' performance in the production process. In particular, we observe that the capability to benefit from spatial spillovers could improve the performance of Southern Italy regions is not allowed by the space-time persistence of the two clusters; hence, Northern-Central Italy cluster, where this effect occurs, never affects Southern Italy cluster. Dualism and capability to benefit from spatial spillovers effect persist also after controlling for the spatial spillovers.

7.5 Conclusion

In this chapter, we have examined the influence of agglomeration externalities and spatial spillovers on the production process of Italian regions. To this purpose, we have estimated a stochastic frontier production function on 20 Italian regions data for the period 1970–1993.

The results point out substantial differences in the Italian macro areas. More specifically, we have verified that localization externalities and urbanization externalities positively affect the productive efficiency of Central and Northern Italy regions. Hence, these results show that production is positively affected by those sectors where the region appears to be specialized and that a higher level of regions diversification favors the production process: "... it is important to make clear that these two externalities are not necessarily opposed, since specialization is a particular feature of a certain sector within a [regions] whilst diversity is a characteristic of the whole area" (Paci and Usai 2000). On the contrary, the efficiency of Southern Italy regions suffers the positive influence only by diversification economies (after taking into account spatial spillovers).

Moreover, the spatial term among the regressors reveals that spatial spillovers have a strong impact in determining a growth of efficiency of the production process. This highlights that the externalities produced in a specific local economy do not exert their effects only within this location but that they cross the boundaries to influence the performance of other locations (Pagnini 2003). In fact, it is rather restrictive to assume that spillover effects run out only within the local economy in which they are generated, and it seems logical to assume that the interdependence degree between these economies is inversely related to distance. In particular, "this spillover effect indicates that the spatial association patterns are not neutral for the economic performances of [Italian] regions. The more a region is surrounded by dynamic regions with high [employment], the higher will be its [productivity]. In other words, the geographical environment has an influence on growth processes. This corroborates the theoretical results highlighted by the New Economic Geography." (Baumont et al. 2001).

Substantial differences among Italian regions arise when we take into account spatial spillovers effects on individual regions. In particular, after considering spatial spillovers, we observe a reduction of the concentration and an increase of the diffusion process of efficiency among Italian regions. For some Northern and Central regions, we can observe, with regard to their capability to benefit from spatial spillovers, that there are some richer regions, which lose efficiency, and some poorer regions, which gain efficiency from the first ones. Furthermore, the spatial analysis of efficiency scores shows a persistent dualism on the regions performance in the production process. In particular, we observe that the capability to benefit from spatial spillovers effect could improve the performance of Southern Italy regions is not allowed by the space-time persistence of the two clusters; in other words, the Northern-Central Italy cluster (where this effect occurs) never affects the Southern Italy cluster.

Another interesting issue is related to the delay with which agglomeration externalities affect production (Combes 2000). In this respect, Henderson (1997) shows that the most significant impacts of localization externalities occur after 3 or 4 years, while those related to urbanization externalities show increased persistence that extends up to 8 years. In future work, we could refer to a dynamic stochastic frontier model estimated by using the generalized method of moments (GMM) (Ahn et al. 1994; Ahn and Schmidt 1995; Ayed-Mouelhi and Goaied 2003; Schmidt and Sickles 1984).

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Chapter 8
Employers' Agglomeration and Innovation in a Small Business Economy: The Italian Case

Giuseppe Croce, Edoardo Di Porto, Emanuela Ghignoni, and Andrea Ricci

Abstract This chapter analyzes the impact of agglomeration on product and process innovation in Italy. Our main goal is to gain a better understanding of the spatial dimension of innovative activities. Based on a unique firm-level source of data provided by ISFOL containing information on employers' personal profiles, we attempt to shed more light into the black box of the local knowledge spillovers. To this end, besides standard density measures, we define and employ an original density indicator and perform a series of IV regressions.

Different from the main strands of the literature on this topic, which envisages positive knowledge spillover effects stemming from agglomeration, we do not find significant evidence that agglomeration fosters innovation. In particular, when small businesses are considered, a negative and significant effect arises. Such evidence suggests that in denser areas detrimental congestion effects tend to prevail and discourage innovation. Moreover, for this subsample of firms, the employers' personal profile prove to be a relevant boost for innovation.

Keywords Product and process innovation • Agglomeration • Knowledge spillovers • Poaching • Employer's education

JEL Classification D83, J24, O18, O31, R23

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8.1 Introduction

Firms and workers are substantially more productive in large and dense urban environments. There is evidence of such agglomeration economies, beyond what can be explained by chance or by the heterogeneity of space, based on the spatial patterns of wages and rents as well as on the direct measurement of how productivity varies across areas (Puga 2010). There is, however, much to learn about the effects of agglomeration economies on specific outcomes. Among them, innovation has particularly attracted researchers' attention in recent times. Overall, the available empirical evidence shows that innovation is not evenly distributed across regions and cities (Audretsch and Feldman 2004). Various theoretical models suggest that agglomeration economies may foster innovation, and the related empirical findings tend to confirm such a positive significant impact.

This chapter offers an empirical analysis based on a unique source of data containing information on individual firms and employers' personal profiles. The main goal of the analysis is to gain a better understanding of the spatial dimension of innovative activities. The analysis focuses on the Italian case which is characterized by a large share of small businesses in low-medium technology industries. Moreover, as reported in Sect. 8.2, previous empirical results for Italy seem to indicate that poaching and other congestion phenomena associated with agglomeration tend to hamper innovation. The empirical test performed in this chapter contrasts the hypothesis of a local learning effect fostering innovation against the opposite hypothesis that in denser areas detrimental congestion effects may prevail and discourage it.

Our results show that in the Italian case, the envisaged positive effect of agglomeration on firms' innovation propensity cannot be taken for granted. On the contrary, when we refer to the smaller firms, a negative effect emerges suggesting that congestion costs outweigh the benefits. We also highlighted the role of the entrepreneurs' personal profiles in innovation, an aspect that is usually neglected in the empirical literature mainly due to the lack of data. In particular, we added the entrepreneurs' individual educational levels as a control in our regressions.

In order to assess the impact of density on innovation, several different specifications of a probit model are regressed. An instrumental variable approach is applied to tackle endogeneity problems and get robust results. Both process and product innovations are considered. Density is measured through various indicators to capture the different possible spillover sources that can influence innovation.

The main novelty of this chapter is represented by focusing the analysis on the employers' human capital. Thanks to the available information; we have attempted to shed more light into the black box of the local knowledge spillovers defining an original density indicator. More precisely, we included and assessed the impact of the local incidence of university graduate employers at province and industry level putting forward as a hypothesis that the human capital of the entrepreneurs may be a relevant factor to explain firms' behavior and outcomes. This may represent a step forward in the search for a more careful understanding of the mechanisms behind spillovers.

The following section motivates our analysis on the basis of the relevant literature on this topic and draws the theoretical framework underlying the subsequent empirical analysis. Then, in the third section, we describe data and provide summary statistics. The fourth section introduces the empirical analysis and reports the main results, while the final one summarizes the main findings.

8.2 Motivations and Literature Background

The idea that agglomeration may enforce learning and consequently innovation is old in economic literature. Marshall argues that agglomerations exist in part because individuals can learn from each other when they live in close proximity. In a seminal work, Glaeser (1999) formalizes Marshall's theory in a model where individuals acquire skills interacting among each other and suggests that dense areas increase the speed of this interaction. From this, it follows that denser locations could represent a better field for the development of new ideas. As an example, Glaeser (1998) reports that "about 96 % of new product innovations occur in metropolitan areas." This suggests that interactions stimulate innovation.[1]

Carlino et al. (2005) provide empirical evidence on the fact that in the USA, all else equal, a city with twice the employment density (jobs per square mile) of another city will exhibit a patent intensity that is 20 % higher. This finding confirms the widely held view that the country's densest locations play an important role in creating the flow of ideas that generate innovation and growth. Such results are corroborated by other works in the literature (e.g., Duranton and Puga 2004; Henderson 2007).

Innovation is not just a linear process generated by scientific and technological research developed in universities' and largest companies' laboratories and implemented in production firms. As Lundvall (1995) argues, innovation stems also from a substantial "learning by interacting," involving a large number of agents connected through formal or informal ties. Accordingly, the extent and the richness of the bundle of the relationships accessible to firms have to be considered as an explanatory factor of the occurrence of innovation. As it was first recognized by Marshall, geographic space is a crucial dimension to define this potential, since a substantial part of the interactions, and of the associated knowledge externalities, occurs as localized phenomena (Audretsch 2003).

The local environment is particularly important for small businesses as they hardly possess all the specialized inputs required to conceive and implement

[1]Cost reduction for moving people, ideas, and products can as well motivate why in denser areas we find a greater propensity to innovate. Hesley and Strange (2002) argue that a dense network of input suppliers facilitates innovation by making it less costly to bring new ideas to fruition.

innovations. Then, compared to larger firms, small enterprises are more dependent on external resources mostly obtainable in the local economy, such as technological consultants, skilled workers, R&D services, cooperation with other firms, and R&D joint ventures (Santamaria et al. 2009). Knowledge is a key resource accruing to the firm largely from the local environment where it operates. Besides knowledge that can be purchased at a price, e.g., through the recruitment of skilled workers, a flow of free knowledge may accrue to every agent located in an area lodging an agglomeration of people and economic activities, provided he/she has enough absorptive capacity.

Such knowledge spillovers spread through formal and informal relationships among entrepreneurs, suppliers, clients, and workers. As for the small firms, these relationships partly coincide with the social network of the entrepreneur which represents a primary factor explaining both the localization choice and the outcomes of the firm (Witt 2004).

In this work, we adopt a broad definition of innovation activities, which encompasses also informal and incremental innovations, problem solving, adaptation of existing technologies, and improvements of processes. This definition fits our empirical analysis, which is based on a sample of Italian firms composed by a vast majority of small and medium-sized businesses belonging to low- and medium-technology industries (for a similar approach see Santamaria et al. 2009).

While most of the literature considers the expenditure in R&D as a proxy for internal resources devoted to innovation, this approach is not really appropriate when a broad definition of innovation, including minor and nonformal innovations, is taken into account. As a consequence, innovations among small businesses have been so far quite a neglected issue. This chapter aims at filling this gap by considering a firm-based sample, which also includes a large fraction of small firms.

The role of external relationships and close spatial proximity for entrepreneurial firms is highlighted by Lechner and Dowling (2003). The location of a firm in denser areas proved to positively affect both the likelihood and the intensity of product innovation in the study by Brouwer et al. (1999) based on Dutch data. In particular, according to their results, innovative activities run by firms located in denser areas are biased towards product innovation, while firms in rural regions are more prone to process innovation. The findings of Fabiani et al. (2005) display that the interactions among firms foster the diffusion of new technologies. By observing nearby firms introducing new products or adopting new processes, an entrepreneur acquires relevant information, which may alleviate the uncertainty about future profitability of innovations. In their review about knowledge spillovers and the spatial distribution of innovation, Audretsch and Feldman (2004) offer further evidence supporting the hypothesis that proximity allows the exploitation of knowledge spillovers. They consider networks and skilled labor mobility among the mechanisms of transmission of spillover.

New technological knowledge spreads more easily within geographical boundaries because it has a relevant tacit and uncodified component, which may flow more effectively through personal contacts (Baptista 2000). As a consequence of such spatial stickiness of knowledge, in areas better endowed with knowledge sources (such as early adopters) and with a higher density of economic agents and activities, innovation tends to be faster (Audretsch 2003). The results shown by Fabiani et al. (2005) on a sample of Italian manufacturing firms indicate that the presence of large firms may foster the adoption of internet-based information and communication technologies. Lopez-Garcia and Montero (2012) find evidence of knowledge spillovers in a study based on a panel of Spanish firms, and Cappelli et al. (2014), on the basis of a sample of German manufacturing firms, show that innovation through imitation may be prompted by spillovers from rival firms.

Fabiani et al. (2005) estimate the impact of the local firm density on innovation and interpret the estimated coefficient as a measure of the *net* effect resulting from the positive effect of the knowledge spillover, on the one hand, and of a possible negative effect due to network externality, on the other hand. Their results show that the positive effect tends to prevail even though in one case the effect is not statistically significant, possibly because the two opposite forces cancel each other.

Despite the evidence provided in the literature largely supports the intuition that local knowledge spillovers exert a positive influence on innovation, the mechanisms behind this influence are not yet fully uncovered. Audretsch and Feldman (2004) conclude their study claiming that further research would be needed to throw more light on this issue.

In our empirical analysis, we try to enter into the black box of the local knowledge spillover. Indeed, besides the influence of the standard measures of density, such as employment density and firms density, in a specification of our model, we consider a more specific and original measure, namely the share of tertiary-graduated employers on the total number of employers in the same province and sector. We suppose that the agglomeration of highly educated employers may constitute a source of knowledge and offer a possible explanation for the existence of spillover.

This idea is consistent with insights from the literature pointing out that the personal profile of the employer is highly influential on a firm's outcomes in general and on innovation adoption in particular, especially as far as small businesses are concerned (e.g., Van der Sluis and van Praag 2008; Doms et al. 2010; Bugamelli et al. 2012). Beker and Hvide (2013) provide evidence that an entrepreneur's individual profile and, more precisely his/her educational level, strongly affects firm growth patterns of both very young firms as well as the more matured ones.

This is hardly surprising as human capital theory predicts that education investment leads to benefits for the individual. Such benefits, in the case of entrepreneurs, do not consist only of a higher income but also a higher firm survival rate and growth. Thus, it seems reasonable to expect that a more educated entrepreneur will also have a higher propensity to sponsor innovation activities; thanks to his/her cognitive and noncognitive abilities. However, due to data limitations, the existing literature on innovation largely neglects the role of the personal characteristics of the entrepreneur. De Mel et al. (2009) assume that the personal profile of the owner might be highly influential in economies with a higher incidence of small and medium enterprises. Their results confirm that more educated owners are more likely to innovate.

We followed a similar approach. So, even though the main focus of our analysis is on the spatially based effects that may originate from an agglomeration of highly educated entrepreneurs, we included the level of education of the employer of each firm in our model. Our hypothesis is that a firm's propensity to innovate may be poorly explained by considering only its sector and size, as it typically occurs in the prevailing approach. Our results (shown in Sect. 8.4) largely confirm this idea as the schooling level of an entrepreneur is proved to be strictly associated with the likelihood of innovation occurrence as far as small firms are concerned.

In our view, if a graduate entrepreneur exhibits on average a higher propensity to innovate, it can be presumed that in local economies with a higher incidence of graduate entrepreneurs, the overall rate of innovations will be higher and, most importantly, the flow of knowledge spread about, and the associated positive externality, will be larger. Hence, we tested whether a higher province density of better educated employers prompts a fiercer spillover effect. In this scheme, the overall effect of agglomeration, which is usually caught by standard density indicators, could partly depend on this more specific source given by the agglomeration of highly educated entrepreneurs.

However, it must be considered that, besides positive externalities, the agglomeration also tends to cause adverse side effects. So, it is necessary, in order to complete our analysis, to take into account the possible congestion effects of agglomeration that might depress local firms' innovation activity, instead of inciting it. Henderson (1986) finds evidence of urban diseconomies. Sedgley and Elmslie (2004) compare both the effects of agglomeration, knowledge spillovers and congestion, on the propensity to innovate in the US economy. A similar approach is followed by Audretsch (2003) who claims that the estimated coefficients of the variables included as proxies for local agglomeration display the *net* effect resulting from the conflict between these two opposite forces.

While congestion phenomena such as overcrowding with a fixed endowment of infrastructure, pollution, and crime may arise in the local economy at large, other congestion effects affect more directly the local labor market as agglomeration may increase the market tightness and push up wages, labor mobility, and poaching, as well as the cost of living and rents (Glaeser 1998).

Combes and Duranton (2006) offer a theoretical model focusing on the trade-off faced by a firm interacting with a cluster of other firms. In their framework, the benefits from the agglomeration are countered by labor poaching, which implies that firms operating in denser areas face both a higher risk of losing skilled workers and higher skilled wages. Even though empirical evidence points out that in general, innovative firms tend to train more intensively their employees (Freel 2003), other papers show that the employer's propensity to invest in workplace training may be depressed by the higher risk of poaching arising in denser areas, which implies a high probability that a trained worker could change job [Brunello and Gambarotto (2007) for UK, Brunello and De Paola (2008) and Andini et al. (2013) for Italy, Muehlemann and Wolter (2011) for Switzerland, and Rzepka and Tamm (2013) for Germany]. Moreover, Bugamelli et al. (2012) report that, according to the opinions of the employers in a number of countries, the lack of qualified workers represents a relevant obstacle to innovation activities. In Italy, in particular, this is one of the main constraints and affects small firms relatively more. The results found by Bugamelli and Pagano (2004) point out that the investments in ICT technologies may be dampened by the lack of complementary investments in the workforce human capital and in the reorganization of the workplace. They conclude that the recruitment of skilled workers imposes costs that are hardly affordable for most of the Italian small and medium firms and therefore may act as a barrier to ICT investment. This suggests that poaching, and congestion effects more in general, affects asymmetrically small and medium-large firms with the former ones suffering the most.

In this regard, it can be argued that, as skilled labor complements innovation, knowledge-intensive businesses with a higher propensity to innovate need qualified human capital to develop their potential (Glaeser 1999; Berry and Glaeser 2005; Ciarli et al. 2012). Hence, it can be expected that the local economies where innovative firms are more concentrated will experience a higher demand for skilled labor and, consequently, higher nominal wages have to be paid to them. Even though skilled labor supply can adjust across areas through mobility, in response to wage differentials, houses and land prices react to changes in local population too. The rise in local rents prompted by the increase in population tends to equalize real wages across areas and halt further adjustments in the quantities of skilled labor. Finally, in a state of equilibrium, denser areas are characterized by higher average skilled wages and rents along with higher productivity (Moretti 2004). Moreover, the rise of wages and rents represent congestion effects which presumably hit chiefly low-productivity firms and, in particular, small businesses.

In the next sections, following the theoretical framework drawn above, we develop an empirical analysis of the effects of agglomeration on the likelihood that innovation occurs at a firm level. Given the aforementioned findings in the economic literature, it seems proper to employ different indicators of agglomeration. In a series of IV regressions, we test separately whether firm density, employment density, and highly educated employers density affect product and process innovations.

8.3 Data and Summary Statistics

The empirical analysis is based on the Employer and Employee Survey (RIL) conducted by ISFOL (the Italian governmental research institute on vocational training) in 2010–2011 on a large representative sample of over 25,000 partnership and limited firms operating in the nonagricultural private sector in Italy. The RIL survey collects a rich set of information about the characteristics of firms, the composition of their workforce, investments on innovation, and other variables that are of minor interest in this analysis. In particular, RIL data allows to connect the information about the firms' propensity to invest in product and process innovation with the human capital endowments of employers and employees (see Table 8.8 in the Appendix for detailed definition of variables).

Moreover, RIL data allows to investigate the behavior of partnership firms, an almost unknown feature of the Italian productive system. To the best of our knowledge, there are no empirical studies based on rich information about a representative sample of both limited and partnership Italian firms, sampled without any industrial, geographical, and dimensional constraints.[2]

As for sample selection, our analysis is limited to firms with more than four employees to guarantee a minimum level of organizational structure. We also excluded those firms which experienced an event of merger or acquisition during the years 2007–2009 in order to minimize the problem of time inconsistency between investment in new processes and products during that period and the characteristics of firms and workers collected by the RIL survey in 2010. This is because mergers and acquisitions might potentially imply a change in the firms' ownership and governance, that is in the characteristics of the employer who decides to invest in new products and processes.[3] Finally, the sample is restricted to observations with no missing data on the key variables, so that the final sample counts 6,259 firms.

The geographical unit of our analysis is the province (NUTS3), which can be seen as a rather fine partition of the Italian territory, and it is largely utilized in empirical works in this field. Due to confidentiality issues, no further refinements of the identification of the area where the firms are located were allowed.

8.3.1 Descriptive Statistics

The descriptive statistics for the variables used in the empirical analysis are displayed in Table 8.1. Given the focus of this chapter, we divide our total sample into two groups: "small firms" with 4–15 employees (3,059) and "medium-large firms" with more than 15 employees (3,200). In addition, we calculated the weighted mean and standard deviations for each of these two groups. As for firms with less

[2]The RIL sample is stratified by size, sector, geographic area, and legal form of firms. The sample design of the RIL Survey involves the use of variable probability of inclusion in the sample, where the range of inclusion depends on firm size, measured by the total number of employees. This choice has required the construction of a "direct estimator," able to take account of the different probability of inclusion among the firms belonging to a specific stratum. In particular, the direct estimator is defined for each sample unit (firm) as the inverse of the probability of inclusion in the sample. The estimates obtained without the use of the direct estimator are, therefore, biased as large firms are overrepresented with respect to their effective incidence in the reference population, having a probability of inclusion in the sample higher than that associated with small firms. Furthermore, the direct estimator has been modified by suitable calibration techniques, obtaining a final estimator calibrated according to a set of constraints. In such a way, this estimator is able to reproduce, through the RIL sample, the total of active firms for each stratum and, simultaneously, the total number of employees in the same stratum (size, sector, etc.).

[3]It is worth noting that in the total sample of firms with at least five employees (14,420), the vast majority (over 13,400) has not experienced any event of merger and/or acquisitions during the period 2007–2009.

Table 8.1 Descriptive statistics

	4 < no. of employees <16		No. of employees >15		Total sample	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Firms' characteristics						
Product innovations	0.34	0.47	0.47	0.50	0.37	0.48
Process innovations	0.28	0.45	0.41	0.49	0.31	0.46
Employer with tertiary education	0.19	0.39	0.32	0.46	0.22	0.42
Family firm	0.94	0.25	0.80	0.40	0.90	0.30
North West	0.27	0.44	0.30	0.46	0.28	0.45
North East	0.28	0.45	0.27	0.44	0.27	0.45
Center	0.23	0.42	0.19	0.39	0.22	0.41
South	0.23	0.42	0.24	0.43	0.23	0.42
4 < no. of employees < 15	1.00	0.00	0.00	0.00	0.72	0.45
14 < no. of employees < 50	0.00	0.00	0.76	0.43	0.21	0.41
49 < no. of employees < 250	0.00	0.00	0.21	0.41	0.06	0.23
No. of employees > 249	0.00	0.00	0.03	0.17	0.01	0.09
Quarrying, mining, etc.	0.00	0.05	0.00	0.04	0.00	0.04
Manufacturing	0.23	0.42	0.37	0.48	0.27	0.44
Gas, water and gas distribution	0.01	0.10	0.01	0.10	0.01	0.10
Construction	0.14	0.35	0.11	0.32	0.13	0.34
Retail and wholesale	0.19	0.39	0.19	0.39	0.19	0.39
Transportation	0.03	0.18	0.04	0.19	0.04	0.18
Hotels and restaurants	0.20	0.40	0.11	0.31	0.18	0.38
Insurance, monetary, and financial intermediation	0.01	0.10	0.01	0.10	0.01	0.10
Real estate and rental	0.05	0.23	0.05	0.22	0.05	0.22
Information, communication, and other business services	0.06	0.25	0.07	0.25	0.07	0.25
Health, education, and social services	0.02	0.14	0.03	0.16	0.02	0.14
Sports, entertainment, and others	0.04	0.19	0.02	0.14	0.03	0.17

(continued)

Table 8.1 (continued)

	4 < no. of employees <16		No. of employees >15		Total sample	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Workers' characteristics						
% tertiary education	0.08	0.16	0.09	0.17	0.08	0.16
% secondary education	0.44	0.31	0.39	0.27	0.43	0.30
% primary education	0.48	0.34	0.51	0.32	0.49	0.34
% trained	0.17	0.32	0.22	0.32	0.18	0.32
HHI_educ	0.67	0.20	0.63	0.18	0.66	0.19
% female	0.41	0.30	0.34	0.27	0.39	0.29
% fixed term	0.20	0.27	0.17	0.24	0.20	0.27
% quits	0.12	0.20	0.06	0.10	0.11	0.18
Local labor markets (prov)						
% employers with tertiary degree(by province and industry)	0.25	0.15	0.27	0.14	0.25	0.16
Firm density 2009 (RIL survey)	0.0018	0.0019	0.0021	0.0022	0.0019	0.0020
Firm density 1981 (Census)	0.26	0.29	0.31	0.34	0.26	0.30
Employment density 2009	1.89	2.23	2.14	2.61	1.96	2.34
% pop. aged 0–20 in 1981	0.30	0.04	0.30	0.04	0.30	0.05
Province size (km^2)	3,186.52	1,777.49	3,117.67	1,761.55	3,204.84	1,792.03
% pop. with tertiary education in 2009	0.13	0.03	0.14	0.03	0.13	0.03
No. of Obs.	3,059		3,200		6,259	

than 15 employees, Table 8.1 makes it apparent that on average, the incidence of firms innovating new products is 34 %, while the incidence of those innovating the productive processes is 28 %. As expected, medium-large firms seems to be more prone to innovation since the average probability that they engage in product innovation is 47 % while in process innovation is 41 %. This constitutes a significant difference in the mean for both types of innovation that we analyze in this study, which is why we prefer to differentiate the analysis in two groups that are likely to be different in their decision to engage in innovation. A possible explanation for this different behavior can be found in the different levels of human capital of the person managing those firms since, according to our data, medium-large firms are more likely on average to be directed by employers with a high educational level. According to our data, no more than 19 % of small firms are managed by an employer with a university degree, while the same percentage rises to 32 % for medium and large firms. This evidence may also be related to the incidence of family ownership, which is large in both groups but somewhat higher for smaller firms (94 % against 80 %). This is not surprising since the management of small businesses is expected to require less formal education and skills than limited and market-owned firms, which are typically characterized by more complex organizational and business structures (Bandiera et al. 2011; Lazear 2010).

Also the human capital of the workforce is quite limited in our sample, coherently with what was highlighted by previous research about the weakness of labor demand for high-skilled workers in Italy (e.g., Naticchioni et al. 2010). Quite surprisingly, in our sample, the distribution of employees' human capital doesn't differ very much between small and medium-large firms. In particular, Table 8.1 shows that the share of employees with a tertiary degree in small firms is only 8 %, while the share of employees with an upper secondary degree is 44 %.

We also took into account the mix of labor input employed in each firm by computing a Herfindahl–Hirschman index (*HHI_educ*) calculated on workforce's schooling at the firm level, which represents a measure of the workforce education diversity (see Appendix for details). Previous results from personnel economics suggest that a more heterogeneous human capital may predict a better firm performance (Garnero et al. 2014). In particular, employers with different skills can use a different mix of labor input. The educational mix of labor employed in medium-large firms appears to be more diverse, according to our measure, by 4 %, suggesting a slightly different use of human capital in the productive process.

Furthermore, the share of employees who have attended a training course organized by the firm is only 17 % for small firms and 22 % for medium-large firms, a result which is in line with both the low propensity of Italian firms to invest in formal training and the positive complementary between training investment and schooling level at workplace (Brunello 2001).

The share of temporary employees and the frequency of voluntary quits are both larger for the smallest firms, revealing that small businesses offer a less favorable workplace and career perspectives for their employees. To complete the picture, Table 8.1 reports that both small and medium-large firms are predominantly localized in the Northern regions and specialized in manufacturing and other service sectors like retail, wholesale, hotels, and restaurants. However, medium-large firms are disproportionally localized in North-West regions (30 %) and are more concentrated in the manufacturing sector (37 %) than what can be found for small firms. To put it differently, the presence of larger firms is favored in those sectors and areas which are presumably more highly intensive in human capital and new technologies.

As for our key local variables, the employment density by province is on average 1.89 and 2.14, respectively, for small and medium-large firms.

The province-industry share of firms managed by an employer holding a university degree, calculated on RIL data, which we denote as locprovsett, is quite similar for the two samples (25 % in small firms and 27 % in medium-large ones). The average value of *locprovsett* is about one-quarter, even though inspection of dataset reveals that its geographical distribution is extremely differentiated by province, ranging between 11 % in Brindisi and 51 % in Milan.

8.4 Empirical Analysis

8.4.1 Econometric Analysis

In order to assess the impact of density on innovation, we regressed several different specifications of an instrumental variable probit model via maximum likelihood techniques. We took into consideration both process innovation (*innov_ proc*) and product innovation (*innov_ prod*). Our dependent variables are dummies with value 1 indicating whether firm *i* has invested in new products or productive processes in the current or past (2 years) period before the RIL survey was conducted. As highlighted in the previous sections, we used different indicators for density aimed at capturing the different possible spillover sources that can influence innovation. More precisely, we used a firm density indicator (*firm_km2)* computed for each province as the number of firms over square kilometers surface, a typical indicator of employment density (*emp_km2*) corresponding to the number of employees over the square kilometers surface, and, finally, our original indicator based on the local employers human capital (*locprovsett*), given by the number of high-skilled employers (where high skilled stands for tertiary degree educated) over the number of firms in a province and sector.

A nonlinear model is needed in our setting as our goal is to test the presence of social interactions (that are described by our density indicators) and the relationship between the spillover effects and the employer decision making. Nonlinearity is a crucial assumption that permits the identification of the spillover coefficient in a cross-sectional setting, whereas a linear model specification would rather suffer from the well-known “Mansky reflection problem” leading to a non-consistent estimation of the density coefficient (Brock and Durlauf 2001). Equation (8.1) is a generic specification for the probit model we will estimate.

$$\Pr\{innov_i = 1\} = \Theta\left(\alpha \cdot man\_col_i + \beta \cdot D_p + \delta \cdot X_i + \varepsilon_i\right) \tag{8.1}$$

Firms settle in different areas, and these locations are heterogeneous. Then, to prevent any inconvenience related to this unobserved heterogeneity, we provide controls for local invariant natural characteristics as well as for characteristics that are location specific, like region (*region FE*), macro-area (*macro-region FE*), and the percentage of graduate population in province *p*, which is a measure of the local human capital (*perc_univ_2009*).

Moreover, we controlled for several firm specific characteristics. The aforementioned *HHI_educ* is a Herfindahl–Hirschman index measuring the homogeneity/diversity of the education level of employees in each firm. The variable *trshare* counts the share of employees that have received workplace training in firm *i*; *fam_ firm* describes whether firm *i* is a family owned firm; *feshare* is the share of female workers in firm *i*, while *ftshare* corresponds to the share of fixed-term contracts in the firm; and *quits* counts the number of voluntary workers quits declared in the survey by the firm.

All the aforementioned control variables are represented by the matrix X_i in Eq. (8.1) and are assumed to be exogenous with respect to our dependent variables.

As discussed before, we take into account that firms may be managed by different types of employers. To this end, we controlled for the employer's individual characteristics which are usually neglected in the empirical literature mainly due to the lack of available data. Indeed, neglecting such information may lead to a non-consistent estimation of the coefficients as a consequence of the presence of unobserved heterogeneity. In particular, we included information about the employer's education level as one of our main covariates in the model. Namely, the variable *man_col* in Eq. (8.1) is a dummy describing if the employer holds a college degree education.

The density variables D_p in Eq. (8.1) are likely to be correlated with unobserved location specific factors that may be also correlated with the error term "ei" leading to a classical endogeneity problem. As a consequence, the estimation of coefficients β is likely to be non-consistent if estimated via the typical maximum likelihood probit model. The adoption of an instrumental variable approach is a possible way to deal with such a problem.

Even though finding good instruments may be difficult, in our specific case, there is an extensive literature on the agglomeration economy that has already considered and discussed possible reliable instruments for specifications similar to Eq. (8.1). For every specification considered, we instrumented a specific density measure with three different instrumental variables. Firstly, the square kilometers of the surface of the province *p* (*km2_110*) is a well-shaped instrument in this context, given that territorial size of an area is exogenously decided and therefore, by definition, cannot be correlated with the error term. This instrument has already been used in a similar context, for example, by Brunello and Gambarotto (2007). Secondly, we used the share of people in the age bracket 0–20 drawn from the 1981 census *(pop_0_20_1981)*. This measure is expected to be strictly correlated with the share of the population currently holding a university degree in province *p*, which represents a good predictor of the share of local entrepreneurs with a university degree. Moreover, this instrument is sufficiently lagged in time not to be correlated with the error term in regression (8.1). A very similar instrument is used in Croce and Ghignoni (2012). Finally, our third instrument is represented by the lagged firm density in province *p*, provided from the 1981 Industry and Services Census data (*firm_km2_81*), that can be taken as a good predictor for firm and employment density and, at the same time, it is sufficiently lagged to be uncorrelated with the error term in Eq. (8.1).

8.4.2 Results

The results for our different specifications are displayed by Tables 8.2, 8.3, 8.4, 8.5, 8.6, and 8.7. Tables 8.2, 8.3, and 8.4 show the results concerning process innovation, while Tables 8.5, 8.6, and 8.7 show estimations related to product innovation.

Table 8.2 Process innovations: firms' density by province (Probit models with instrumental variables)

	(1)	(2)	(3)	(4)
	Employees > 4 and < 16		Employees > 15	
Variables	IV2 stage	IV1 stage	IV2 stage	IV1 stage
HHI_educ	−0.373***	−0.000	−0.599***	0.000
	(0.145)	(0.000)	(0.161)	(0.000)
trshare	0.540***	−0.000	0.501***	−0.000
	(0.076)	(0.000)	(0.081)	(0.000)
man_col	0.191***	−0.000	0.029	−0.000*
	(0.059)	(0.000)	(0.061)	(0.000)
educ1_tot	−0.138	0.000	−0.062	0.000
	(0.154)	(0.000)	(0.168)	(0.000)
educ2_tot	0.087	0.000	0.141	−0.000
	(0.100)	(0.000)	(0.114)	(0.000)
fam_firm	0.075	−0.000	0.141**	−0.000
	(0.102)	(0.000)	(0.067)	(0.000)
feshare	−0.191*	0.000	0.171	0.000
	(0.100)	(0.000)	(0.134)	(0.000)
ftshare	0.025	0.000	−0.082	−0.000
	(0.105)	(0.000)	(0.128)	(0.000)
quits	−0.162	0.000	−0.592**	−0.000
	(0.116)	(0.000)	(0.277)	(0.000)
perc_univ_2009	1.672**	0.003	−1.667*	−0.000
	(0.799)	(0.004)	(0.917)	(0.005)
firm_km2_81		0.007***		0.007***
		(0.000)		(0.000)
pop_0_20_1981		−0.003		−0.004
		(0.006)		(0.006)
km2_110		0.000		0.000
		(0.000)		(0.000)
firm_km2	−36.295***		−16.900*	
	(12.491)		(9.826)	
Constant	−0.698***	0.000	0.408	0.001
	(0.251)	(0.002)	(0.274)	(0.002)
industry FE	Yes	Yes	Yes	Yes
region FE	Yes	Yes	Yes	Yes
macro-region FE	Yes	Yes	Yes	Yes
Observations	3,059	3,059	3,200	3,200

Robust standard errors in parentheses
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 8.3 Process innovations: employment density by province (Probit models with instrumental variables)

	(1)	(2)	(3)	(4)
	Employees > 4 and < 16		Employees > 15	
Variables	IV2 stage	IV1 stage	IV2 stage	IV1 stage
HHI_educ	−0.372**	−0.007	−0.601***	−0.070
	(0.145)	(0.020)	(0.160)	(0.044)
trshare	0.541***	0.009	0.501***	−0.021
	(0.076)	(0.012)	(0.080)	(0.013)
man_col	0.193***	0.025**	0.030	−0.002
	(0.059)	(0.010)	(0.061)	(0.008)
educ1_tot	−0.141	0.018	−0.067	−0.007
	(0.154)	(0.028)	(0.168)	(0.037)
educ2_tot	0.086	0.008	0.143	0.041
	(0.100)	(0.014)	(0.114)	(0.025)
fam_firm	0.076	−0.002	0.142**	0.004
	(0.102)	(0.020)	(0.066)	(0.012)
feshare	−0.193*	−0.037*	0.168	−0.035**
	(0.100)	(0.020)	(0.135)	(0.017)
ftshare	0.023	0.035	−0.080	0.027
	(0.105)	(0.025)	(0.128)	(0.025)
quits	−0.166	−0.001	−0.592**	0.037
	(0.117)	(0.021)	(0.277)	(0.034)
perc_univ_2009	1.682**	4.605*	−1.635*	4.202**
	(0.785)	(2.413)	(0.904)	(1.688)
firm_km2_81		7.381***		7.633***
		(0.304)		(0.167)
pop_0_20_1981		2.733		2.700**
		(1.970)		(1.268)
km2_110		0.000**		0.000**
		(0.000)		(0.000)
emp_km2	−0.032***		−0.015*	
	(0.011)		(0.009)	
Constant	−0.709***	−1.653***	0.403	−1.545***
	(0.252)	(0.555)	(0.274)	(0.390)
industry FE	Yes	Yes	Yes	Yes
region FE	Yes	Yes	Yes	Yes
macro-region FE	Yes	Yes	Yes	Yes
Observations	3,059	3,059	3,200	3,200

Robust standard errors in parentheses
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 8.4 Process innovations: share of college graduate employers by province and economic sector (Probit models with instrumental variables)

	(1)	(2)	(3)	(4)
	Employees > 4 and <16		Employees >15	
Variables	IV2 stage	IV1 stage	IV2 stage	IV1 stage
HHI_educ	−0.370***	0.004	−0.606***	−0.007
	(0.143)	(0.006)	(0.164)	(0.008)
trshare	0.535***	−0.006	0.502***	0.001
	(0.078)	(0.004)	(0.073)	(0.004)
man_col	0.223***	0.030***	0.041	0.017***
	(0.077)	(0.004)	(0.067)	(0.003)
educ1_tot	−0.128	0.013	−0.051	0.028***
	(0.166)	(0.010)	(0.199)	(0.010)
educ2_tot	0.082	−0.002	0.145	0.004
	(0.091)	(0.004)	(0.103)	(0.006)
fam_firm	0.071	−0.008	0.142**	−0.002
	(0.098)	(0.006)	(0.065)	(0.003)
feshare	−0.204*	−0.015***	0.182	0.019***
	(0.112)	(0.006)	(0.132)	(0.006)
ftshare	0.007	−0.013*	−0.085	−0.008
	(0.126)	(0.007)	(0.149)	(0.011)
quits	−0.166	−0.004	−0.603**	−0.020**
	(0.126)	(0.006)	(0.289)	(0.010)
perc_univ_2009	2.257	0.816***	−1.085	0.871***
	(1.851)	(0.183)	(1.731)	(0.230)
firm_km2_81		0.138***		0.159***
		(0.026)		(0.026)
pop_0_20_1981		−0.525**		−0.513**
		(0.211)		(0.231)
km2_110		0.000***		0.000***
		(0.000)		(0.000)
locprovsett	−1.108		−0.647	
	(1.043)		(0.732)	
Constant	−0.520**	0.222***	0.489*	0.208***
	(0.262)	(0.064)	(0.275)	(0.075)
industry FE	Yes	Yes	Yes	Yes
region FE	Yes	Yes	Yes	Yes
macro-region FE	Yes	Yes	Yes	Yes
Observations	3,059	3,059	3,200	3,200

Robust standard errors in parentheses
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 8.5 Product innovations: firms density by province (Probit models with instrumental variables)

	(1)	(2)	(3)	(4)
	Employees > 4 and < 16		Employees > 15	
Variables	IV2 stage	IV1 stage	IV2 stage	IV1 stage
HHI_educ	−0.337**	−0.000	−0.806***	0.000
	(0.139)	(0.000)	(0.153)	(0.000)
trshare	0.458***	−0.000	0.383***	−0.000
	(0.069)	(0.000)	(0.071)	(0.000)
man_col	0.178***	−0.000	−0.031	−0.000*
	(0.053)	(0.000)	(0.062)	(0.000)
educ1_tot	0.378**	0.000	0.533***	0.000
	(0.155)	(0.000)	(0.158)	(0.000)
educ2_tot	0.251***	0.000	0.377***	−0.000
	(0.095)	(0.000)	(0.101)	(0.000)
fam_firm	0.183**	−0.000	0.051	−0.000
	(0.084)	(0.000)	(0.057)	(0.000)
feshare	−0.145	0.000	0.317***	0.000
	(0.099)	(0.000)	(0.100)	(0.000)
ftshare	0.132	0.000	0.207	−0.000
	(0.109)	(0.000)	(0.152)	(0.000)
quits	−0.075	0.000	0.200	−0.000
	(0.106)	(0.000)	(0.202)	(0.000)
perc_univ_2009	2.365***	0.003	−1.375	−0.000
	(0.826)	(0.004)	(0.984)	(0.005)
firm_km2_81		0.007***		0.007***
		(0.000)		(0.000)
pop_0_20_1981		−0.003		−0.004
		(0.006)		(0.006)
km2_110		0.000		0.000
		(0.000)		(0.000)
firm_km2	−46.700***		−13.075	
	(15.022)		(12.971)	
Constant	−1.178***	0.000	0.249	0.001
	(0.217)	(0.002)	(0.285)	(0.002)
industry FE	Yes	Yes	Yes	Yes
region FE	Yes	Yes	Yes	Yes
macro-region FE	Yes	Yes	Yes	Yes
Observations	3,059	3,059	3,200	3,200

Robust standard errors in parentheses
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 8.6 Product innovations: employment density by province (Probit models with instrumental variables)

	(1)	(2)	(3)	(4)
	Employees > 4 and < 16		Employees > 15	
Variables	IV2 stage	IV1 stage	IV2 stage	IV1 stage
HHI_educ	−0.338**	−0.007	−0.807***	−0.070
	(0.139)	(0.020)	(0.153)	(0.044)
trshare	0.459***	0.009	0.384***	−0.021
	(0.069)	(0.012)	(0.071)	(0.013)
man_col	0.180***	0.025**	−0.030	−0.002
	(0.053)	(0.010)	(0.062)	(0.008)
educ1_tot	0.375**	0.018	0.528***	−0.007
	(0.154)	(0.028)	(0.157)	(0.037)
educ2_tot	0.250***	0.008	0.378***	0.041
	(0.095)	(0.014)	(0.101)	(0.025)
fam_firm	0.186**	−0.002	0.052	0.004
	(0.084)	(0.020)	(0.057)	(0.012)
feshare	−0.147	−0.037*	0.316***	−0.035**
	(0.099)	(0.020)	(0.100)	(0.017)
ftshare	0.131	0.035	0.209	0.027
	(0.109)	(0.025)	(0.152)	(0.025)
quits	−0.078	−0.001	0.201	0.037
	(0.106)	(0.021)	(0.202)	(0.034)
perc_univ_2009	2.318***	4.606*	−1.408	4.202**
	(0.820)	(2.414)	(0.968)	(1.688)
firm_km2_81		7.381***		7.633***
		(0.304)		(0.167)
pop_0_20_1981		2.734		2.700**
		(1.970)		(1.266)
km2_110		0.000**		0.000**
		(0.000)		(0.000)
emp_km2	−0.041***		−0.010	
	(0.012)		(0.011)	
Constant	−1.187***	−1.654***	0.251	−1.544***
	(0.215)	(0.555)	(0.284)	(0.390)
industry FE	Yes	Yes	Yes	Yes
region FE	Yes	Yes	Yes	Yes
macro-region FE	Yes	Yes	Yes	Yes
Observations	3,059	3,059	3,200	3,200

Robust standard errors in parentheses
$***p < 0.01$, $**p < 0.05$, $*p < 0.1$

Table 8.7 Product innovations: share of college graduate employers by province and economic sector (Probit models with instrumental variables)

	(1)	(2)	(3)	(4)
	Employees > 4 and < 16		Employees > 15	
Variables	IV2 stage	IV1 stage	IV2 stage	IV1 stage
HHI_educ	−0.327**	0.004	−0.811***	−0.007
	(0.137)	(0.006)	(0.172)	(0.008)
trshare	0.443***	−0.006	0.384***	0.001
	(0.075)	(0.004)	(0.072)	(0.004)
man_col	0.245***	0.030***	−0.016	0.017***
	(0.071)	(0.004)	(0.056)	(0.003)
educ1_tot	0.401**	0.013	0.556***	0.028***
	(0.162)	(0.010)	(0.194)	(0.010)
educ2_tot	0.241***	−0.002	0.382***	0.004
	(0.088)	(0.004)	(0.103)	(0.006)
fam_firm	0.165*	−0.008	0.051	−0.002
	(0.090)	(0.006)	(0.059)	(0.003)
feshare	−0.173*	−0.015***	0.330***	0.019***
	(0.102)	(0.006)	(0.114)	(0.006)
ftshare	0.100	−0.013*	0.203	−0.008
	(0.114)	(0.007)	(0.154)	(0.011)
quits	−0.082	−0.004	0.185	−0.020**
	(0.103)	(0.006)	(0.208)	(0.010)
perc_univ_2009	4.364**	0.816***	−0.400	0.871***
firm_km2_81		0.138***		0.159***
		(0.026)		(0.026)
pop_0_20_1981		−0.528**		−0.514**
		(0.209)		(0.231)
km2_110		0.000***		0.000***
		(0.000)		(0.000)
locprovsett	−2.201**		−0.775	
	(0.928)		(0.666)	
Constant	−0.895***	0.223***	0.314	0.209***
	(0.247)	(0.063)	(0.292)	(0.075)
industry FE	Yes	Yes	Yes	Yes
region FE	Yes	Yes	Yes	Yes
macro-region FE	Yes	Yes	Yes	Yes
Observations	3,059	3,059	3,200	3,200

Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

In every table, the first two columns report the coefficients and the standard errors for the small firms' sample. In column 2, in particular, the results are reported from the first stage regression in which the endogenous covariate is regressed on X_i and the three aforementioned instruments. Column 3 and 4 display the estimated coefficients for the medium-large firms. Column 4, in particular, shows the results from the first stage regression. Tables 8.2 and 8.5 refer to the specification in which D_p is the firm density indicator, Tables 8.3 and 8.6 report the estimates when the employment density (*emp_km2*) is included. Tables 8.4 and 8.7, lastly, show the results for the specification where our original density indicator (*locprovsett*) is included.

According to the theoretical framework discussed in Sect. 8.2, and in line with the interpretations offered by previous papers, the coefficients related to the density variables have to be taken as a measure of the *net* effect arising as a result of the two opposite influences exerted by agglomeration: on one hand, the possible positive influence of the knowledge spillover and, on the other hand, the negative one deriving from congestion and poaching.

As for process innovation, we find negative and significant coefficients for two of the three density indicators considered. Only the variable *locprovsett* provides negative but not significant results for both small and medium-large firms, whereas both firm and employment density coefficients point out a negative and statistically significant effect on innovation.

The obtained negative net effect reveals that congestion costs pass over the benefits deriving from agglomeration. This seems to be particularly the case of smaller firms, which show more significantly negative coefficients of the density variables, apart from *locprovsett*. The more intense effect of congestion on small-size enterprises is hardly surprising since, as argued above, they are likely to suffer mostly from fiercer competition in the local markets for inputs that complement innovation. In particular, they may face more difficulties to attract and retain skilled labor, which represents a fundamental requirement to implement innovation.

Instruments work very nicely and result to be not weak in all specifications as shown in Tables 8.2, 8.3 and 8.4 (the f tests for the first stage regression are always greater than 10). Despite the good performance of the instruments, the coefficient of our original density indicator *locprovsett* results to be not significant. This suggests that in this case, the two agglomeration effects counterbalance, thus no correlation is detected by the density coefficient. Compared to the negative and statistically significant net effect detected by the other density indicators, we may presume that in areas where better educated employers agglomerate, innovation benefits from more intense positive spillover. Indeed, the nonsignificance of *locprovsett* suggests that the negative impact of congestion tends to be countervailed by the positive influence of spillover. According to our theoretical framework, this seems to support our claim that a higher local density of better educated employers may act as an additional specific source of positive spillover.

With regard to product innovation, the findings shown in Tables 8.5, 8.6, and 8.7 reveal that the effect of density is always negative and significant for smaller firms, while it remains not significant for larger firms. The instruments are in line with previous regressions and prove to be not weak. Again, these results further support the view that small businesses are disproportionately affected by the costs of congestion and from higher relative price of specialized inputs that are complements to innovation.

The reported results are consistent with findings provided in a recent paper on Italian local labor markets by Andini et al. (2013), who found that local density raises labor turnover (conditional on the type of employment) as well as the share of voluntary quits which may be interpreted as proof that congestion increases with agglomeration. Furthermore, their results confirm the hypothesis of a relationship between agglomeration and poaching, while providing only weak support to the notion of local learning associated with density. Overall, these elements suggest that congestion effects of agglomeration tend to be more relevant than the beneficial effects of it in the Italian context.

Our results suggest that small firms suffer from congestion effects arising in urban areas, where wages and other local input prices tend to be higher. The pattern of localization of innovative firms in Italy revealed by our findings shows that such activities are not attracted solely by metropolitan or denser areas and tend to be disseminated over the territory. This is in line with previous researches for Italy that have noted that there is no tough hierarchical order between larger and medium urban areas according to the production of innovations (Trigilia and Ramella 2010).

As for the other main covariates, it is worth noticing that the coefficient associated with the employer's human capital dummy (*man_col*), which describes whether or not the employer holds a college degree, is positive and significant in all the estimates regarding small firms, while it is always far from being significant for larger firms. All else equal, employer's education seems to make the difference in innovation propensity just among small businesses.

Moreover, the larger the share of workforce with a high or intermediate educational level (*educ1_tot* and *educ2_tot*), the higher the likelihood that the firm runs product innovations, both in small and in medium-large ones, however, density is measured.

The *HHI_educ* variable, which was included to control for workforce composition, indicates that firms characterized by a greater workforce educational diversity tend to invest more in product as well as process innovations. This is in line with previous results predicting that firms' productivity is positively affected by diversity (Garnero et al. 2014). Moreover, as expected on the basis of previous results in the empirical literature (Santamaria et al. 2009; Lopez-Garcia and Montero 2012), the larger the share of workers taking part in workplace training activities (*trashare*) in the firm, the higher the likelihood that the firm engages in innovation. This result holds true in whatever specification, for both small and medium-large firms, with regard to process as well as product innovation. A possible interpretation for this evidence is that training fosters the firm's propensity to innovation by enabling its absorptive capacity.

The effects associated with the remaining controls included in the estimated equations are weaker or less stable.

8.5 Final Remarks

This chapter analyzes the impact of agglomeration on product and process innovation across Italian provinces. In a series of IV regressions, we make use of a new unique source of information provided by ISFOL. This new set of data makes it possible to control for individual entrepreneurial characteristics and provincial agglomeration effects. We consider both process and product innovations and employ different measures of agglomeration in order to test through which means agglomeration effects work out. We do not find significant evidence that agglomeration fosters innovation. According to our results, it emerges that in Italy, agglomeration does not exert any substantial *net* positive effect on the probability that private sector firms undertake innovative activities. In particular, innovation by the smaller firms is even depressed when they are located in denser areas, however density is measured. Thus, it must be concluded that congestion and poaching effects tend to prevail over the possible positive influences of agglomeration envisaged by theoretical literature. Standard tests confirm that our analysis proves to be robust and reliable.

Moreover, employer's education turns out to be a significant factor associated with innovation when a sample of smaller firms is considered. This supports our claim that an individual employer's profile should always be taken into account in this kind of analysis.

Several other attempts to study the effect of agglomeration on innovation in Italy have to be undertaken. Quite a substantial improvement on empirical grounds could be reached by observing the innovation pattern throughout different years, taking advantage of a panel structure of data. This is the research proposal we aim to carry out when ISFOL panel data will be available.

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Appendix

Table 8.8 Variables definition

Variables	Definition	Sources[a]
innov_ proc	Dummy variable that equals 1 if the firm has introduced process innovation over the past 3 years, 0 otherwise	(a)
innov_ prod	Dummy variable that equals 1 if the firm has introduced product innovation over the past 3 years, 0 otherwise	(a)
HHI_educ	Herfindahl–Hirschman index on employees' education levels[b]	
Trshare	Share of employees that have attended a training course organized by the firm (on the number of firm's employees) in 2009	(a)
man_col	Dummy variable that equals 1 if an employer has a tertiary level of education, 0 otherwise	(a)
educ1_tot	Share of employees with a tertiary education degree (on the number of firm's employees)	(a)
educ2_tot	Share of employees with an upper secondary education degree (on the number of firm's employees)	(a)
fam_ firm	Dummy variable that equals 1 for family firms, 0 otherwise	(a)
feshare	Share of female employees (on the number of firm's employees)	(a)
ftshare	Share of fixed-term contracts (on the number of firm's employees)	(a)
quits	Number of employees who voluntarily quitted the firm in 2009, on total number of employees	(a)
perc_univ_2009	Share of population (15–64 years old) with a tertiary education degree by province, 2009	(b)
firm_km2	Number of firms per square kilometer by province, 2009	(a)
emp_km2	Number of employees per square kilometer by province, 2009	(b)
locprovsett	Share of tertiary educated employers by province and industry on total number of employers in the same province and sector	(a)
firm_km2_81	Number of firms per square kilometer by province in 1981	(d)
pop_0_20_1981	Share of population aged between 0 and 20 years by province in 1981, on total population by province in 1981	(c)
km2_110	Size of the 110 Italian provinces (NUTS 3), in square kilometers	(e)
industry FE	Eleven economic sector: Quarrying, mining, etc.; Manufacturing; Gas, water and gas distribution; Construction; retail and wholesale; Transportation; Hotels and restaurants; Insurance, monetary, and financial intermediation; Real estate and rental; Information, communication, and other business services; Health, education, and social services; Sports, entertainment, and others	(a)
region FE	Twenty Italian regions (NUTS 2)	(a)
macro-region FE	Four macro-areas: North West, North East, Center, South and Islands	(a)

[a] *Sources*: (a) RIL-ISFOL Survey 2010; (b) ISTAT; Labor Forces, 2009; (c) ISTAT; Population Census 1981; (d) ISTAT; Industry and Services Census 1981; (e) http://www.tuttitalia.it/province/superficie/

[b] $HHI = \sum_{i=1}^{3} s_i^2$ where s_i (i = 1, 2, 3) is the share of employees with tertiary/upper secondary/less than upper secondary education degree

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Part III
Differences in Human Capital and R&D

Chapter 9
Do FDI in Business Services Affect Firms' TFP? Evidence from Italian Provinces

Massimo Armenise, Giorgia Giovannetti, and Gianluca Santoni

Abstract This chapter studies the effect of FDI in business services on total factor productivity (TFP) of Italian manufacturing firms, over the period 2003–2008. More precisely, the chapter tests the presence of vertical linkages between foreign business professionals and domestic manufacturing firms. Our results, robust to different specifications, show that foreign capital inflows in business services improve the performance of domestic manufacturing firms. This relationship is particularly strong in the case of high-tech sectors, such as mechanics and machinery. Traditional sectors, on the other hand, seem to be less sensitive to the availability of foreign business services in the same location.

Keywords Business services • FDI • Manufacturing • Panel data • Productivity

JEL classification: C23, D24, F23

9.1 Introduction

The choice of Multinational Corporations (MNCs) to invest in a country is often considered an indicator of the country's attractiveness. However, over the past two decades, a large part of the literature has maintained that reducing market entry

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barriers to attract foreign firms could result in significant benefits for host countries: higher growth, productivity, technology transfers, etc.,[1] since MNCs are likely to generate knowledge spillover and have several other interaction mechanisms with local firms.

Such positive externalities, especially in the case of developing countries, are also likely to have an important impact on the labor market. Foreign capital inflows can enhance firms productivity generating an increase in the demand for skilled labor and a decrease in that for unskilled labor, triggering best practices for human resources management (Driffield et al. 2009).

The impact of FDI on domestic firms depends, however, on the linkages they are able to generate. Badinger and Egger (2010) suggest that vertical linkages between domestic and multinational firms are particularly important. Kugler (2006) highlights the highest potential of vertical and inter industry FDI knowledge spillovers. In the case of horizontal FDI, foreign-owned suppliers are likely to be less interested in transferring knowledge, because of potentially stronger competition.

The existing empirical literature highlights positive spillovers resulting from foreign direct investments in services and inter-industry (Fernandes and Paunov 2012; Giovannetti et al. 2010; Lileeva 2010).

In line with this literature, this chapter provides evidence in support of positive spillovers for Italy, where FDI in business services have only recently become relevant but are still understudied. Italy is an interesting case since for long time, it lagged behind other OECD countries in attracting FDI. Only in the last decade, this situation has been (slowly) changing; against stable (or decreasing) foreign direct investment in manufacturing—still low compared to competitors—foreign investments in *"business services"*[2] increased substantially. Between 2001 and 2007, the number of foreign firms investing in professional business services in Italy passed from 1,277 to 1,700, and the number of their employees from less that 200,000 to around 300,000 (see ISTAT 2010a).

Given the relatively small size of Italian firms and a persistent productive specialization in so-called traditional low-tech goods—the most challenged by globalization—FDI in business services can potentially have a very strong positive impact on Italy's competitiveness and on domestic employment. The possibility for manufacturing firms to use (upstream and downstream) services (R&D, post-sales

[1]See for all, BarbaNavaretti and Venables (2006), Markusen (1989) and Blalock and Gertler (2008).

[2]Business services include services to other businesses ranging from accounting and legal services to industrial cleaning. For the purposes of this chapter, the business services sector is statistically defined as a subset of Section K in the national accounts, including computer and related activities, research and development, and other business activities' Standard Industrial Classification (sic) codes 72–74—it also includes elements of telecommunications and services classified in sections I and J.

strategies, local legal know etc.), expensive to internalize and often not readily available, may mitigate the negative TFP trends recently recorded in Italy.[3]

In what follows, we confine our attention to FDI in business services in Italy with the aim of assessing their possible role in enhancing manufacturing productivity. We cover the period 2003–2008, use firm level data and consider the effect of foreign capital on productivity. Though in line with the approach of Ayyagari and Kosová (2010), we increase the geographical disaggregation, by performing the analysis at the (Italian) provinces level. More precisely, we estimate how the foreign presence in business services in a given province, and in a given year, may affect the performance of the domestic manufacturing firms operating in the same province, in terms of productivity (measured as total factor productivity—TFP). The results show that TFP of Italian manufacturing firms is positively related to FDI in the business services sector. The relationship is stronger for some high-tech firms (mechanics, machinery and equipment) than for the so-called traditional "Made in Italy" products (textiles, footwear etc.). This positive correlation underscores the importance of attracting international investments in business services.

The positive effect on firms TFP triggers a recomposition of labor demand towards skilled labors, which in the long run is likely to positively affect employment and wages. In the short run, the demand for unskilled labors in some sectors is likely to decrease; the overall effect may still be positive (also in the short-run), if in other sectors labor demand increases through backward and forward linkages. The ability to attract foreign professionals might be particularly important for those provinces—especially in the South of Italy—lagging behind in terms of efficiency and employment rate (see the recent survey by Pastore 2013).

The chapter is structured as follows. Section 9.2 briefly summarizes the existing literature. Section 9.3 describes data and summary statistics. The econometric model and results are in Sect. 9.4. Section 9.5 concludes. An appendix provides further descriptive evidence and support tables.

9.2 The Related Literature

The literature on the effects of FDI in business services on the host economy is relatively new.[4] Until recently, most studies, focussed on FDI on manufacturing. FDI in business services, however, seems to be more likely to lead to improvements

[3] According to the ISTAT (2010b): "between 2000 and 2009, total factor productivity (TFP) has declined (−0.9 % per year on average), due to a negative trend in the value added (−0.2 %) and a positive development of the productive inputs (average annual growth of 0.8 %). In particular, since 2000 it is possible to recognize three stages corresponding to different trends: a negative trend in 2000–2003 (−1.3 % annual average), a moderately positive dynamic in the years 2003–2007 (0.6 % annual average) and a marked reduction in the period 2007–2009 (−3.4 % annual average)".

[4] According to UNCTAD (2004), FDI in services has been increasing at high rates from the end of the 1990s. Different subsectors, however, had different developments. Business sectors have had the highest rate of growth.

in the quality of services available to manufacturing firms, as well as increase their supply (i.e., their variety) and lower their costs, thereby enhancing manufacturing competitiveness.

There are several ways through which FDI in business services could benefit manufacturing firms[5]: first, through standard channels of knowledge spillovers.[6] Second, as Fernandes and Paunov (2012) put it: "Manufacturing firms benefit from pecuniary spillovers if increases in the quality or variety of the services they use due to FDI are not fully appropriated by service providers" (p. 308). Those pecuniary spillovers[7] might become knowledge spillovers, if downstream users of these (new and possibly improved) services apply the embodied knowledge to improve their own TFP (see Branstetter 2001).

The impact of FDI on domestic firms, however, depends crucially on the linkages they generate. Kugler (2006) highlights that one can expect a larger potential, at least for knowledge spillovers, from vertical and inter industry FDI. In the case of horizontal FDI, foreign-owned suppliers are likely to be less interested in transferring knowledge because of stronger competition fears. FDI in business services are more likely to generate vertical spillovers (both backwards and forward) on manufactures. Foreign suppliers can provide inputs, assistance, and after sales services to domestic firms, allowing them to access better (and possibly previously unavailable) services and competencies. Rodriguez-Clare (1996), formalizing the effects of the different linkages, assumes that production benefits from the use of specialized inputs, and that proximity of suppliers is key for all those services that need a "face-to-face" interaction: auditing, consulting, wholesale services, machine repair, after sales services, etc. Proximity improves the quality of information, as well as the strength of signalling, therefore, decreasing or avoiding that "wait and see" attitude that disrupts investments in situations of uncertainty.

If there are no adequate domestic providers for the services needing a "face-to-face" interaction, firms have to rely on foreign inflows and there is room for foreign investors to exploit profit opportunities. Only the use of better and more detailed firm level data[8] allowed to find empirical support for the theoretical models developed

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[5]To see better this point, think of a country with inadequate services that negatively affect firms' performance. Arnold et al. (2008) provide several examples of dysfunctional services and their impact on African firms. Unstable telecommunication services affect coordination with clients and suppliers; inadequacies of banking services may prevent a firm from investing; power cuts can disrupt production etc.

[6]By knowledge spillovers, we mean "knowledge" created by a multinational, and used by the domestic firm and not necessarily entailing full compensation to the MNC. We include managerial skills, organization of production; know how, better marketing and distribution, transfer of technical skills etc.

[7]By pecuniary spillover, we mean nominal gains resulting from quality increases not necessarily reflected in prices.

[8]It has also been suggested that FDI spillovers (both positive and negative) have a limited geographical dimension or, at least, that they decrease with (physical) distance (Audretsch and Feldman 1996; Audretsch 1998; Keller 2002; Madariaga and Poncet 2007), as channels of

along these lines. According to Eschenbach and Hoekman (2006), countries where services are liberalized tend to grow faster due to the increase in the number and quality of business services available for manufacturing users. Francois and Woerz (2008) maintain that the increased openness of business services between 1994 and 2004 had strong positive effects on exports, value added, and employment in OECD countries. Fernandes and Paunov (2012) claim that 7 % of the increase in TFP of Chilean firms can be traced back to FDI in services; furthermore, capital inflows in services also foster innovation activity in manufacturing, allowing "laggard to catch up with leaders" (p. 305). Fernandes (2009) finds positive and significant effects of liberalization of financial services and improvement in infrastructures on labor productivity of downstream manufacturing industries in Eastern European countries. Using firm-level data, Arnold et al. (2011) find significant and positive effects of services liberalization on manufacturing firms' TFP in the Czech Republic; Arnold et al. (2010) have similar results for manufacturing in India; Blalock and Gertler (2008) find a positive impact for Indonesia; Javorcik (2004) for Lithuania; Li and Javorcik (2008) provide evidence of a positive effect on the TFP of manufacturing suppliers to the retail sector for Romania; and Lileeva (2010) finds that an increase in US FDI to Canada increases productivity growth in domestically controlled plant and that the effects are more pronounced for plants that buy more science-based intermediate inputs.

In line with this literature, in what follows, we explore the impact of business services capital inflows on the productivity of Italian firms, with a specific focus on vertical linkages.[9]

9.3 Data and Summary Statistics

We construct an original database by merging information from different data sources. We merge firm level data balance sheets information from the Bureau Van Djick "AIDA" dataset,[10] for the period 2003–2008, with information on the location of foreign direct investment in Italy from ICE-REPRINT.[11]

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technological diffusion are reinforced at the regional level (Girma and Wakelin 2001; Girma 2005; Ayyagari and Kosová 2010). We do not deal with the issue of distance, but some empirical evidence for Italy can be found in Mariotti et al. (2011).

[9]To our knowledge, the study of the impact of FDI in business sector in Italy is limited to Nicolini and Piscitello (2009) and Mariotti et al. (2011).

[10]AIDA data set reports the balance sheets of Italian corporations with a value of production greater than roughly 800,000 euro, http://www.bvdep.com.

[11]REPRINT is the census of the foreign affiliates with a turnover higher than 2.5 million euros per year and provides information on the starting date of the operations for all manufacturing and business services affiliates, see Mariotti and Mutinelli (2010). We consider as business services FDI: Logistics, information technology and software design, and professionals services; GDP data come from ISTAT.

Data from the Bureau Van Djick "AIDA" are used to get a measure of productivity of Italian firms over the same period. ICE-REPRINT data allows us to identify foreign affiliates as well as the timing and province of the location choice.[12] Controlling for possible measurement errors, we end up with an unbalanced panel of 63,773 firms.[13] More than 75 % of firms in our sample are small or medium (below 50 employees); only 3.3 % are large (over 250).[14]

We measure manufacturing firms' TFP, defined as a nonparametric measure, using a multilateral index approach based on the Tornquist index proposed by Caves et al. (1982). More in detail, our TFP measure is given by the following expression:

$$\begin{aligned}\ln\Phi_{it} - \overline{\ln\Phi_t} = & \left(\ln Y_{it} - \overline{\ln Y_t}\right) \\ & - \left(\frac{s^l_{it} - s^l_t}{2}\right)\left(\ln L_{it} - \overline{\ln L_t}\right) \\ & - \left(1 - \frac{s^l_{it} + s^l_t}{2}\right)\left(\ln K_{it} - \overline{\ln K_t}\right)\end{aligned} \tag{9.1}$$

where $\ln\Phi_{it}$ is the productivity of firm i at time t expressed as deviation from the 2-digit sector specific averages (identified with bar). The variable Y represents the firm's value added, L the number of worker, and K the physical capital.[15] The parameter S^l_{it} represents the share of the labor cost L_{it} on total added value Y_{it} of the firm i at time t, and can be interpreted as a technology parameter (VanBiesebroeck 2007).[16] Projecting the average TFP of manufacturing firms on the Italian province

[12]Please see Figs. 9.4–9.8 in Appendix for more descriptive statistics on the characteristics of foreign owned firms in Italy.

[13]We exclude observations for which value added, employment, and capital are missing, negative or null. Furthermore we "clean" our sample from outliers, dropping the extreme 1 % values for the distribution of the following variables: capital intensity, yearly capital intensity growth rate, yearly capital growth rate and yearly employment growth rate.

[14]A comparison of the distribution of firms from our database for different years, sectors, and Provinces (NUTS3) with the distribution of firms registered by Chambers of Commerce shows a strong correlation. The Unioncamere (Chambers of Commerce) dataset covers all the active firm in a given year and province, by 2 digit Ateco 2002 (national version of NACE rev 1.1), but does not contain any further information about the firms. The correlation with our dataset, calculated with Pearson and Spearman Indices, spans from 0.82 for sector/year/province (Person) to 0.97 for year/province (Spearman). Complete results are available on request. Hence, firm level data used in constructing our productivity measure seems to be a good approximation of the true population of firms across provinces and sectors.

[15]Nominal series have been deflated using sector-specific price indexes from the National statistical institute, ISTAT.

[16]This index allows a comparison of firms performance within a specific sector without imposing a common technology to the firms belonging to the same sector. The relative weights of the production factors are individually measured and reflect the different production technology at firm level and the flexure of the single production functions adopted by the firms. In the case of semi-parametric estimation à la Olley and Pakes (1996) or Levinsohn and Petrin (2003), these

map gives an idea of the productivity differences and dynamics within the country (see Fig. 9.1): firms operating in the North of Italy are, on average, more productive than those South of Rome. Over time, only firms in the center and North East improve their productivity. Firms in the South keep lagging behind.

Also the location choice of foreign investors is polarized. Projecting the Province share[17] of foreign business services firms on the Italian map (Fig. 9.2) suggests that the North is preferred by foreign investors, relatively to the Center, and especially to the South of Italy. A comparison between the productivity of firms belonging to a province with a presence of foreign investors in business services and that of firms producing in a province with no foreign presence (see Fig. 9.3) suggests a positive relation between business services presence and firm productivity. Moreover, the difference of productivity between firms (of the same industry) operating in province with presence of foreign professionals tend to increase over time.

Figures 9.1 and 9.2 suggest the presence of common pattern between TFP and FDI concentration distributions; specifically, manufacturing firms located in Northern provinces seem to have a higher productivity level and host a higher number of foreign multinationals. The higher average productivity in the North could be due to differences in internal firms' factors (managerial ability, workers

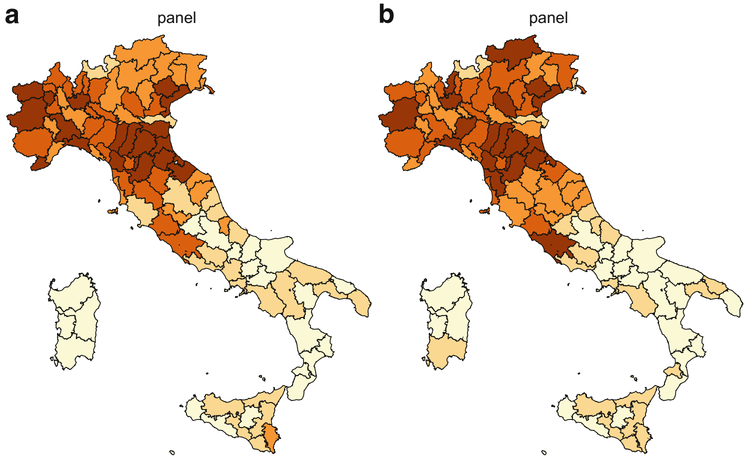

Fig. 9.1 Mean TFP of manufacturing firms by Province. *Note*: year 2001 is reported in panel (**a**), year 2006 in panel (**b**); higher data values are darker, each cluster contains 20 % of the distribution. The distribution refers to manufacturing sectors, since each firm productivity is computed with respect to a hypothetical firm (given by the sector average, in inputs, outputs, and technology), we do not need to control for the sectoral composition of the province manufacturing sectors

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relative weights are assumed to be identical and are estimated as equal for every firm in a same industry with a precision loss.

[17]The share is computed as the number of business services FDI in province j at time t over the total number of business services FDI in Italy at time t.

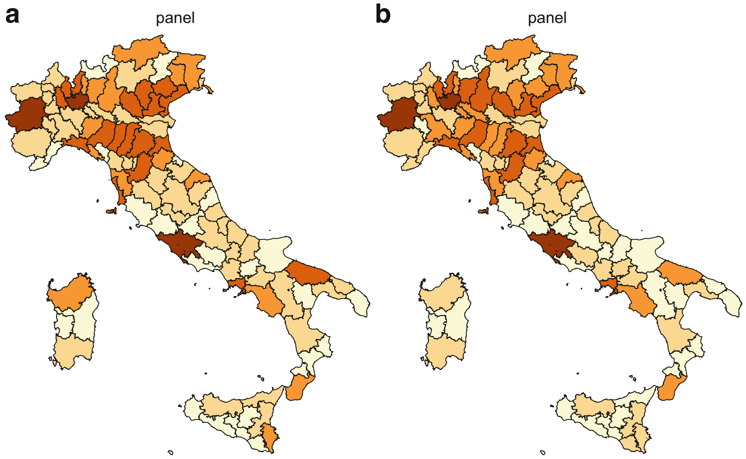

Fig. 9.2 Province share of total foreign business services firms operating in Italy. *Note*: year 2001 is reported in panel (**a**), year 2006 in panel (**b**); higher data values are darker, the first group contains the provinces with No foreign firms. Note that in 2001, 26 provinces have no foreign investments in business services; in 2006, 28. The first positive break point contains 25 % of the distribution, the second 50 %, the third 75 %, and the darker regions encompass provinces with a share higher than 95 % of the distribution

skills, and innovation) as well as external factors (better infrastructures, financial deepening, better trained human capital, etc.)[18]; furthermore, the access to foreign professional services could play an important role. The preference for the North is likely to be correlated with the relative size of the local market, general business conditions, and the presence of (better) infrastructures. Another important determinant of this "cluster structure" could be the relative higher efficiency of firms in the North. But the causal relation could also go in the opposite direction, namely a larger presence of logistics, ICT and other kind of services and professionals in a specific location may have a positive impact on production. To further investigate this issue, we turn to an econometric model.

9.4 Empirical Strategy and Main Results

9.4.1 The Empirical Model

Theoretical and empirical works on the effects of FDI suggest that domestically controlled plants are more likely to benefit from supplier and customer linkages with foreign producers than from intra-industry knowledge spillovers from foreign

[18]For a review of the impact on productivity of internal and external factors, see Syverson (2011).

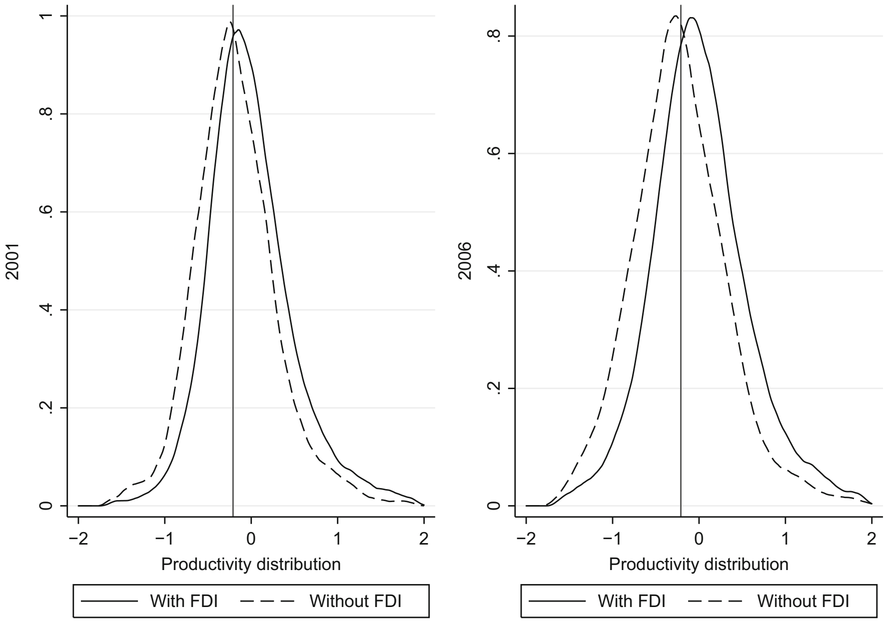

Fig. 9.3 Productivity distribution with and without business services FDI. *Note*: year 2001 is reported on the *left panel*, year 2006 on *right panel*; the *vertical line* refers to the median productivity of manufacturing firms in 2001 operating in a province with no foreign investors in Business Service

competitors. As pointed out by Rodriguez-Clare (1996), and mentioned above, a firm producing final goods could benefit from having access to a wider variety of specialized inputs. Foreign multinationals specialized in business services are likely to increase the variety as well as the quality of locally available services, above all, if the home and the host countries are not too different.

To test the impact of foreign business professionals on domestic manufacturing firms, let us consider a standard Cobb–Douglas production function[19]:

$$Y_{it} = \Phi_{it} K_{it}^{\alpha} L_{it}^{\beta} \tag{9.2}$$

where Y_{it} is the value added for firm i at time t, Φ_{it} is the TFP, K_{it} the capital stock and L_{it} the labor force of plant i at time t. We assume that TFP of firm i depends on a set of firm characteristics X_{it}, as well as on "external factors"[20] (such as business services) Γ_{jt} and on an error term ϵ_{it}.

[19] In what follows we make use of a slightly modified version of Martin et al. (2011) specification.

[20] See Syverson (2011).

Given the very high spatial heterogeneity of the Italian economy, the variables on the local business environment are measured at the Province level j (NUTS3). Since the size effect of the modifiable areal unit problem (MAUP) might be important, especially at large scales, we use the smallest geographical and administrative unit available for both FDI and TFP[21]:

$$\Phi_{it} = (\Gamma_{jt})^{\gamma}(X_{it})^{\delta}\epsilon_{it} \tag{9.3}$$

Taking natural logarithms of Eqs. (9.2) and (9.3), we obtain:

$$y_{it} = \alpha k_{it} + \beta l_{it} + \Phi_{it} \tag{9.4}$$

$$\Phi_{it} = \gamma\Gamma_{jt} + \delta X_{it} + \epsilon_{it} \tag{9.5}$$

We can then write:

$$\Phi_{it} = \alpha_i + X_{it}^{'}\delta + \Gamma_{jst}^{'}\gamma + \eta_{st} + \epsilon_{it} \tag{9.6}$$

where subscripts i, j, t, and s refer to firm, province, year, and industry,[22] respectively. Φ_{it} is the log TFP productivity index of the manufacturing firm i at time t. The vector Γ_{jst-2} contains the variables describing the local business environment, with respect to foreign incidence in business services as well as manufacturing sectors, plus other controls on the province level characteristics as concentration of sales, urbanization, and labor productivity on services (both foreigns and natives).

Our main variable of interest is the foreign incidence in business services (FBS_{jt-2}), measured by the ratio of foreign business services turnover on overall service sector GDP in province j at time $t-2$. This measure, highlighting that foreign firms are suppliers of specialized inputs for domestic final good producers, allows us to identify potential vertical influences.

As a control on the provinces' attractiveness, affecting the multinationals distribution, we use a measure of the extent of foreign presence in the manufacturing sectors: FMS_{jst-2} (i.e. the foreign presence in manufacturing sector s, in province

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[21]On the issue see Briant et al. (2010). Note that the mean area of Italian provinces is 2,816 km^2 with a coefficient of variation of 0.17; while French departments and Spanish provinces have a mean area of 5,666 km^2 and 10,118 km^2, respectively, with a much higher coefficient of variation, 0.33 (France) and 0.47 (Spain).

[22]In our empirical analysis we consider 20 sectors of Manufacture, Section D (NACE rev 1.1), in detail: 15 Food and beverages, 17 Textiles, 18 Wearing Apparel, 19 Leather (luggage etc.), 20 Wood (except furniture), 21 paper Products, 22 Publishing and printing, 24 Chemicals, 25 Rubber and plastics, 26 Non metallic minerals, 27 Basic metals, 28 Fabricated metal products (except machinery), 29 Machinery, 30 Office machinery and computers, 31 Electrical machinery, 32 Communication equipment, 33 Optical instruments, 34 Vehicles, 35 Other transports, 36 Furniture and others manufactures.

j, at time $t-2$). It is computed as the turnover of foreign firms in industry s and province j at time $t-2$ over the turnover of sector s in province j at time $t-2$.[23] This variable could possibly allow the identification of horizontal externalities.[24] Other controls used are: (1) a Herfindahl–Hirschman index, built on the distribution of sales (HH_{jst}), measuring the degree of competition in a given province and sector; (2) a time varying index of economic density, $\ln(Pop/km^2)_{jt-2}$, in order to control for the degree of urbanization[25]; (3) a measure of the average productivity in services (the value added per person employed, $\ln(VAs/Emp)_{jt-2}$).[26] Finally, since firms operating in highly competitive sectors may have a better technological capacity, we also include a full set of sectoral specific time trends η_{st}.

Table 9.1 shows the summary statistics.

In what follows, most of the local business environment variables (in vector Γ'_{jst}) are lagged 2 years to mitigate endogeneity issues.[27] This seem to be consistent also with the idea that, even if a firm becomes aware of the local availability of a new set of inputs (or technology), it may take time to incorporate them in the production process.

The vector X'_{it} contains control variables at firm level[28] due to Italy's peculiar productive structure. The geographical distribution of some variables of interest highlights the gap of Southern Italy, especially with respect to TFP and "Foreign shares". In order to single out this effect, we use a dummy, *South*, equal to one for provinces south of Rome (see Guiso et al. 2004) interacted with our main variable of interest $\ln(FBS_{jt-2})$.

Finally ϵ_{it} is a stochastic error term capturing the determinants of TFP omitted from the model, considering that relevant investment choices are not independent at the firm level, we clustered standard errors at firm level, in order to control for

[23]The overall turnover of the sector s, province j and time t is computed using firm level data from the AIDA dataset.

[24]Most provinces have an average manufacturing industries share relatively small, less than 1 %, even if there are some remarkable exceptions, such as Prato, where the economic structure is skewed towards Textiles. It is worth noting that in Prato textiles represented over 18 % of the economic activity in 2001 (and has had a declining trend, to 12 % in 2006), and more than 56 % of total manufactures. In Lecco, manufacture of fabricated metal products represents around 7.5 % of the whole economic activity of the province and nearly 35 % of manufacturing.

[25]Highly agglomerated provinces are likely to be on average more productive and so foreign firms may decide to locate in such provinces in order to exploit agglomeration externalities. This might bias the estimated coefficient. For this reason, we decide to include also this variable. The data necessary to build this indicator come from ISTAT.

[26]In fact, the higher productivity of the manufacturing firms could be caused from the presence of an overall services sector more developed and efficient in a given province; data coming from ISTAT.

[27]With the only exception of HH_{jst}.

[28]The variables used as control are: log of age and age squared, plus a categorical variable of firm size, all contemporaneous to the TFP measure. Size is built on the distribution of sales by sector and year, this variable consist in 5 classes each of them encompasses 20 % of sales distribution. All these data coming from AIDA.

Table 9.1 Summary statistics, 2003–2008

Variables	Obs	Mean	North (mean)	Center-South (mean)	Std. dev	Min (2008)	Max (2008)
HH	10,126	0.32	0.29	0.37	0.22	0.01	0.99
Density	618	252	286	224	356	38	2,632
Serv. Prod	618	51	55	49	5.1	48	65
FBS (%, services GDP)	434	2.9	3.75	1.31	5.5	0.02	41.8
FBS (%, total GDP)	434	1.93	2.67	1.00	4.2	0.01	30.3
Foreign business							
Services firms	9,864	21.63	32	9	103	1	897
Domestic							
Manufacturing firms	63,733	1,081	1,351	380	1,072	7	4,328
TFP (mean centered)	63,733	0	0.05	−0.12	0.52	−4.8	5.7

Note: Density is in levels, reporting the number of resident by squared kilometer; Serv. prod is the value added per person employed in the service sector (1,000 euros). FBS (both in terms of market share and firm incidence) considers only provinces with at least one foreign firm in business services. Eighty-three provinces have at least one FDI in business services (68 of that for the entire period). All the variable reported are computed by year and province. Source for foreign business services firms refers to the number of firms in ICE-REPRINT. Source for domestic firms refers to the number of firms in AIDA. In TFP, case observations refer to the number of firms potential errors autocorrelation as well as heteroscedasticity. Since some explanatory variables in our estimation are potentially correlated with time invariant firm characteristics, we estimate our baseline Eq. (9.6) using firms fixed effects.

9.4.2 Regression Results

Results for our benchmark model are reported in Table 9.2, column (1). Firm level controls have the expected sign and are statistically significant. Age is positively correlated to TFP, with diminishing returns over time. In particular, the productivity

Table 9.2 Fixed effects results, dependent variable TFP

	(1)	(2)	(3)	(4)
Age	0.516***	0.515***	0.515***	0.516***
	(0.0310)	(0.0310)	(0.0310)	(0.0310)
Age2	−0.177***	−0.177***	−0.176***	−0.177***
	(0.0125)	(0.0125)	(0.0125)	(0.0125)
Size	0.0934***	0.0935***	0.0935***	0.0935***
	(0.00280)	(0.00280)	(0.00280)	(0.00280)
FBS	0.430***	0.341***	0.385***	0.433***
	(0.0777)	(0.0789)	(0.0857)	(0.127)
FMS	0.0967	0.0890	0.0834	0.0903
	(0.419)	(0.423)	(0.423)	(0.423)
HH	−0.0153	−0.0179	−0.0172	−0.0174
	(0.0139)	(0.0139)	(0.0139)	(0.0140)
Density		0.182***	0.207***	0.181***
		(0.0604)	(0.0623)	(0.0604)
Serv. Prod.		−0.178***	−0.175***	−0.182***
		(0.0516)	(0.0516)	(0.0516)
FBS*South			−0.342*	
			(0.202)	
FBS*Size				−0.0226
				(0.0248)
Sect. time trend	Yes	Yes	Yes	Yes
N. observations	201,815	201,815	201,815	201,815
R squared	0.849	0.849	0.849	0.849

Note: Interaction terms variables are mean centered before computing the interactions. All covariates are in natural logs, except for HH_{jst} so they may be interpreted as elasticities. Standard errors are clustered by firm identifier. The period covered is 2003–2008. All regressions include an intercept, not reported
*, **, *** Statistically significant at the 10, 5, and 1 % level, respectively

gain reaches the maximum when the firm age is around 4 years.[29] This result appears to be consistent with Branstetter (2001). Firm size is positive and significant implying that firms in the right tail of sales distribution are on average more productive.

The impact of the foreign presence in the same manufacturing sector is not statistically different from zero; this is consistent with previous findings (Javorcik 2004; Kugler 2006) underlying how spillovers from foreign presence do not act horizontally, since foreign firms tend to avoid information leakages to their domestic competitors. Our measure of vertical linkages ($\ln(\text{FBS}_{jt-2})$) is positive and statistically significant. This means that more foreign professionals in an area could support the improvement of the overall production process for a domestic firm via the optimization of logistics or the improvements in ICT and R&D, as well as professional consulting.

Columns (2)–(4) in Table 9.2 include additional covariates aiming to control for agglomeration externalities ($\ln(\text{Pop}/\text{km}^2)_{jt-2}$) and systematic differences in the overall service efficiency ($\ln(\text{VAs}/\text{Emp})_{jt-2}$). Both result to be positively correlated with TFP. More importantly, including this additional controls does not affect the significance or the magnitude of the foreign business services measure coefficient. This suggests that the results are not driven by sectoral composition or by systematic differences in the degree of urbanization and service efficiency.

Given the high degree of spatial heterogeneity characterizing Italy (see Figs. 9.1 and 9.2), we decided to check whether our results are driven by the joint distribution of the TFP and FBS, both skewed towards higher values in the North. To do so, we interact our main variable of interest with the dummy *South*.[30] Results are reported in Table 9.2 column (3). The direct effect is positive and strongly significant, while the interaction coefficient is negative, but weakly significant, suggesting that the positive effect of foreign professionals on domestic manufacturing productivity is weaker for southern firms but still positive. This seems to confirm that the results are not affected by the common geographical pattern of the variables of interest. Local availability of services (such as transportation, trade financing, as well as insurance and accounting) has a positive impact on domestic manufacturing firms productivity. A firm can obtain these services either by buying them from service providers (often foreign) or internalizing them. Internalizing, however, may involve a fixed cost that only the more productive firms may be able to pay. In Table 9.2, column (4), we test if the impact of local business services availability is different for firms of different sizes, by interacting our variable of interest with the firm size. The coefficient for the interaction is not statistically significant suggesting that

[29]Since the variable is expressed in log, the maximum gain in productivity related to the firm age is at $X^* \approx 1.46$.

[30]In specifications with the interaction terms, the interacted variables are always centered (zero mean).

the impact of local provision of specialized inputs, i.e., of business services, is not decreasing in firm size.[31]

9.4.3 Sectoral Analysis

In our analysis, we use firm level data from 20 different manufacturing sectors of the NACE classification.[32] Different manufacturing sectors are likely to be affected in different ways by foreign investments in business services (as also by the simple availability of some specific Business Services). To check to what extent the presence—if any—of foreign firms in business services affects firm productivity differently across sectors, as a first approximation, we exploit the information of our database separating industry subgroups characterized by different technology level and use of services as intermediate inputs: textiles and furniture, chemicals, fabricated metal products, machinery and equipment, electronics, vehicles, and transport equipment. Textile and furniture are typical *"Made in Italy"*, mature, low technology sectors, characterized by a relative intensity of unskilled labor force. The others could be considered as a good proxy for high-tech sectors.

Results for sectoral estimates are reported in Table 9.3. The main results hold: size coefficients are positive and significant for all the sectors, and the marginally decreasing positive effect of age on productivity also holds across sectors. However, there are some interesting differences. Our main variable of interest $\ln(\mathrm{FBS}_{jt-2})$ is strongly significant only for some high-tech sector and insignificant (though with the expected positive sign) for the traditional, low-tech *"Made in Italy"* sectors. This suggests that vertical linkages are likely to be stronger in the case of high tech sectors, when firms are better equipped to exploit the positive externalities. Interestingly, the $\ln(\mathrm{FMS}_{jt-2})$ coefficient is negative and significant for *"Machinery and equipment"* suggesting that in those industries competitive pressure of foreign firms is stronger.

[31] Since the variables of interest of foreign presence vary at aggregate level (province by year) while the dependent variable is at firm (year) level, we are aware of the possible distortion in the Standard errors, see Moulton (1986). There are number of ways to correct this, the most widely used is to apply a arbitrary variance-covariance matrix at an higher cluster level (cluster command in Stata). Given the structure of our data, with an high variability in the number of firms by cluster (province-year) the asymptotic properties of the variance estimator needed are not verified. Angrist and Pischke (2008) and Wooldridge (2008) suggest using a two-step estimator. We followed this procedure and our results do not change, result available upon request.

[32] Rev. 1.1. For the sector list see footnote 21.

Table 9.3 Sectoral heterogeneity, dependent variable TFP

	Textiles and furniture	Chemicals	Fabricated metal products	Machinery and equip.	Electronics	Vehicles and transport equip.
Age	0.610***	0.645***	0.432***	0.567***	0.560***	0.443**
	(0.0744)	(0.115)	(0.0656)	(0.0751)	(0.100)	(0.174)
Age2	−0.210***	−0.217***	−0.141***	−0.194***	−0.198***	−0.152**
	(0.0304)	(0.0452)	(0.0266)	(0.0310)	(0.0424)	(0.0728)
Size	0.104***	0.0755***	0.0979***	0.0875***	0.104***	0.101***
	(0.00791)	(0.0102)	(0.00539)	(0.00690)	(0.00946)	(0.0149)
FBS	−0.154	0.128	0.459***	0.717***	0.638**	0.551
	(0.213)	(0.235)	(0.170)	(0.209)	(0.254)	(0.502)
FMS	−8.169	2.381	0.204	−1.404***	0.804	−0.249
	(15.39)	(2.648)	(1.937)	(0.542)	(0.671)	(0.449)
HH	−0.0559	−0.0323	0.0474	0.0177	−0.0173	−0.00430
	(0.0433)	(0.0424)	(0.0366)	(0.0389)	(0.0368)	(0.0459)
Density	0.626***	−0.00293	0.255	0.426*	0.126	0.384
	(0.215)	(0.161)	(0.160)	(0.253)	(0.286)	(0.400)
Serv. Prod	−0.372***	−0.390**	−0.0613	−0.251*	−0.364**	0.0295
	(0.145)	(0.165)	(0.104)	(0.132)	(0.176)	(0.319)
Sect. time trend	Yes	Yes	Yes	Yes	Yes	Yes
N. observations	30,915	19,877	44,057	29,764	18,606	5,731
R squared	0.861	0.863	0.825	0.841	0.849	0.861

Note: All covariates are in natural logs, except for HH_{jst}, so they may be interpreted as elasticities. Standard errors are clustered by firm identifier. Standard errors are clustered by firm identifier. The period covered is 2003–2008. All regressions include an intercept, not reported

*, **, *** Statistically significant at the 10, 5, and 1 % level, respectively

9.5 Conclusions

Business services are an important component of the competitiveness of a country, not only because of their direct effect on the economy but also their impact on manufacturing. We analyze the effect of foreign direct investment in business services on the TFP of Italian manufacturing firms, to see to what extent—if any—these investments improve firms' productivity. Our results, consistent across provinces and sectors and several econometric specifications, show that FDI in business services has a positive impact on TFP, therefore, suggesting that the service sector may turn out to be an important source of positive externalities (also through FDI). Manufacturing firms, especially high tech, seem to be able to concentrate on the production process and a more efficient management if they can rely on external services provided in the province where they produce.

The development of the business services sector allows manufacturing firms to outsource tasks and activities to specialists who can perform them at lower costs and possibly better. While this is true in general, for Italy the business services sector depends crucially on foreign inflows and, at the same time, the reduced size of Italian firms means that for them to outsource is much more feasible than trying to internalize the services (too costly).

FDI in business services allows to enhance firms' economic performance, and their effect differs depending on the level of technology of the sectors and on the availability of skilled labor in the province. At firm level, outsourcing business services activities indirectly increases the efficiency of the production process. More importantly, at national level, the presence of increasing FDI in business services could enhance the competitiveness of the economic system. The presence of foreign business professionals might also have a significant effect on labor demand. The increase in efficiency in the production process, in fact, is likely to generate a greater market for skilled labor and, as a result, a growth in employment and wages in the long run. This might imply that for some provinces, it might be particularly important to attract foreign investors in business services to trigger a possible catching-up process. The improvement in TFP, due to the availability of possibly new services, allows firms to better respond to a highly competitive environment. Hence, to reduce the barriers still protecting FDI in services may turn out to be a positive sum game; foreign service providers can bring in new technologies and know how to provide services needed by Italian manufacturing firms to keep (or enhance) their competitiveness. To attract these investments, however, the Italian system should improve the overall business environment, reducing the number of cumbersome bureaucratic practices. Furthermore, provinces, especially in the South, must make sure to have skilled labor not to lose opportunities.

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Appendix

1 Foreign-Owned Business Service Firms in Italy: Some Graphs

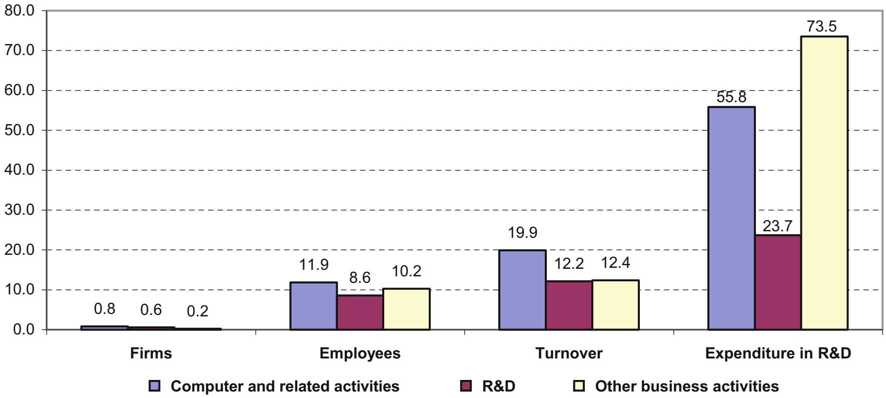

Fig. 9.4 Share of Foreign-controlled firms (%, 2007). *Source*: ISTAT

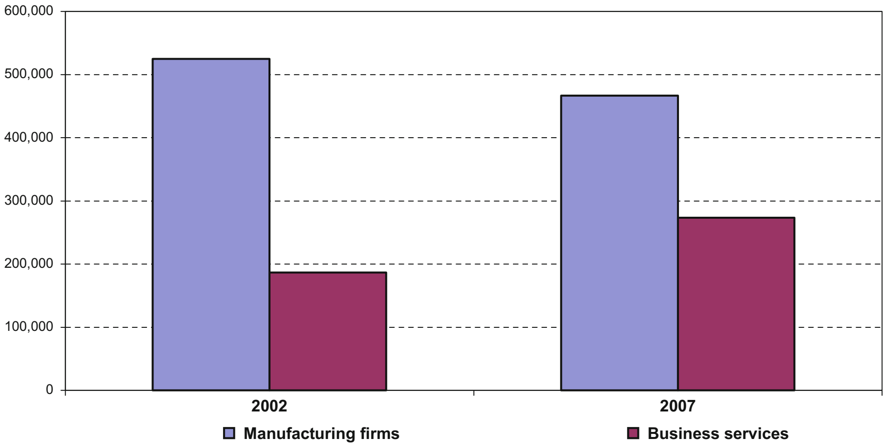

Fig. 9.5 Number of employees in Foreign-owned firms. *Source*: ISTAT

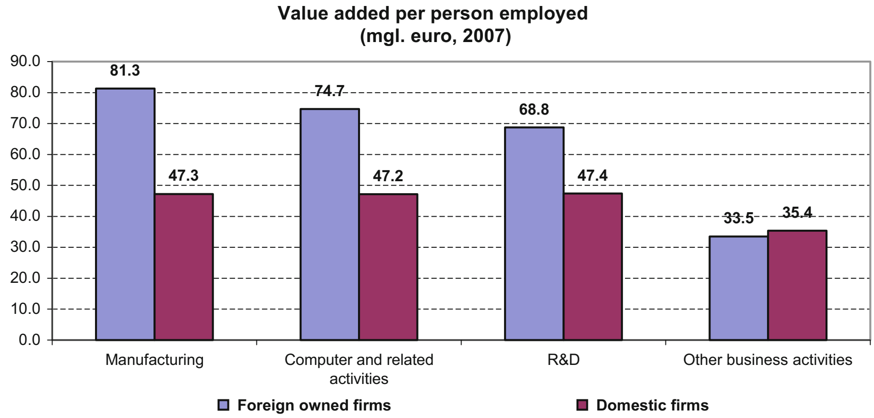

Fig. 9.6 Value added per person employed (1,000 euro, 2007). *Source*: ISTAT

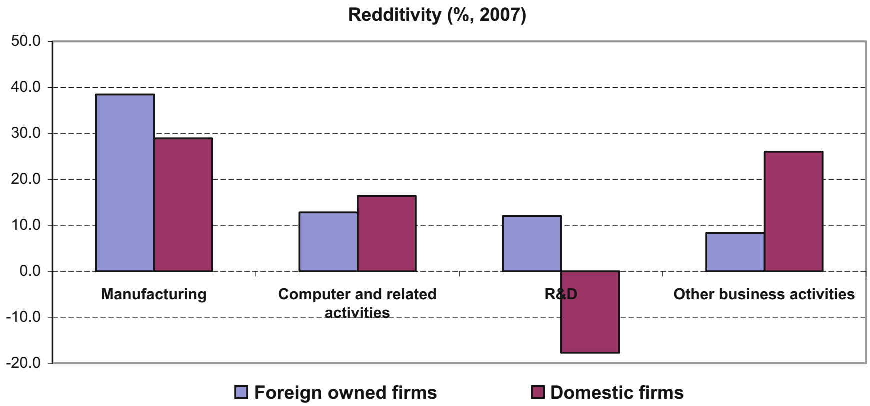

Fig. 9.7 Profitability (%, 2007). *Source*: ISTAT

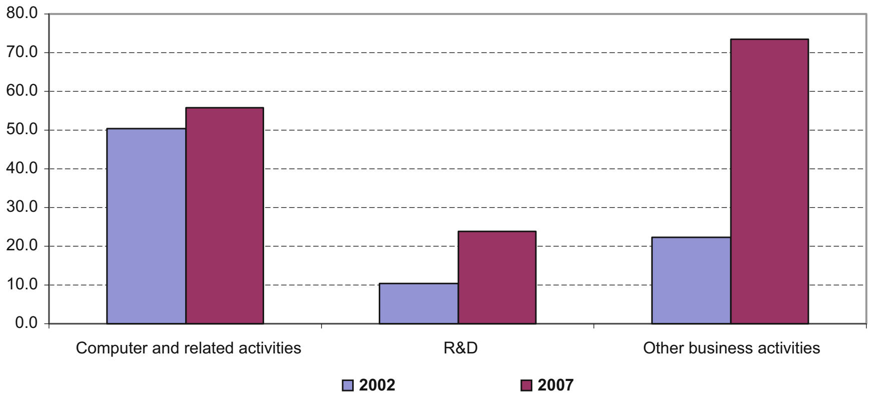

Fig. 9.8 Share of Foreign-controlled firms' R&D expenditure. *Source*: ISTAT

2 Robustness of Different Clustering Levels

We test the robustness of our results to different clustering levels, aiming to check if cross-sectional dependence in the error term may invalidate our findings. Results are reported in Table 9.4, the first column reports standard errors (SE) clustered at firm level, as in our baseline regression, just for comparison purposes. In column (2)–(4), SE are clustered by year and different geographical level, estimated coefficients of $\ln(FBS_{jt-2})$ are statistically significant, at conventional levels, throughout different cluster specification, suggesting that cross-sectional dependence seems not to invalidate our results.

Table 9.4 Fixed effects results, dependent variable TFP

	Firms identifier (1)	NUTS3 by year (2)	NUTS2 by year (3)	Macro-Region by year (4)
Age	0.515***	0.515***	0.515***	0.515***
	(0.0310)	(0.0291)	(0.0426)	(0.0473)
Age2	−0.177***	−0.177***	−0.177***	−0.177***
	(0.0125)	(0.0117)	(0.0168)	(0.0199)
Size	0.0935***	0.0935***	0.0935***	0.0935***
	(0.00280)	(0.00254)	(0.00429)	(0.00547)
FBS	0.341***	0.341*	0.341**	0.341**
	(0.0789)	(0.189)	(0.138)	(0.149)
FMS	0.0890	0.0890	0.0890	0.0890
	(0.423)	(0.308)	(0.309)	(0.315)
HH	−0.0179	−0.0179	−0.0179	−0.0179
	(0.0139)	(0.0128)	(0.0120)	(0.0120)
Density	0.182***	0.182*	0.182	0.182
	(0.0604)	(0.0978)	(0.151)	(0.169)
Serv. Prod.	−0.178***	−0.178	−0.178*	−0.178*
	(0.0516)	(0.141)	(0.104)	(0.0913)
Sect. time trend	Yes	Yes	Yes	Yes
N. observations	201,815	201,815	201,815	201,815
R squared	0.849	0.849	0.849	0.849
N. clusters	63,773	618	120	30

Different clustering strategies

Note: Interaction terms variables are mean centered before computing the interactions. All covariates are in natural logs, except for HH_{jst} so they may be interpreted as elasticities. Standard errors are clustered by firm identifier. The period covered is 2003–2008. All regressions include an intercept, not reported. Macro region classifies national territory into five groups, North-East, North-West, Center, South, and Islands

*, **, *** Statistically significant at the 10, 5, and 1 % level, respectively

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Chapter 10
Explaining the Patenting Propensity: A Regional Analysis Using EPO-OECD Data

Claudio Cozza and Francesco Schettino

Abstract The aim of this chapter is to conduct an empirical study of the patenting propensity at the European regional level using the OECD-REGPAT dataset. We use patent applications by inventor's region as, in this case, linkage to the territory is stronger than using applicant's region. Data analysis reveals the existence of a deep, uneven distribution of patent applications, R&D expenditure and human capital. Richer regions show higher levels of both private and public R&D expenditure as well as a consistent share of the total European patent applications. Starting from the analysis of these key variables, we proceed explaining the determinants of patenting propensity. The results substantially confirm the significant role of R&D expenditure on patenting activity: mainly the business enterprises, but also the government sector component. Human capital variables show similar positive effect, while average enterprise size seems not to play a determining role in patent applications.

Keywords Patents • Intellectual property rights • Innovation • EPO • R&D

JEL Classification O34, K29, O4, O53, K19

10.1 Introduction

Several scholars have investigated various aspects of the patenting process as a means of depicting the multifaceted nature of innovation. Their studies fall into two groups: those inquiring into the qualitative features of patents and their value and those investigating the determinants of patent application. Griliches (1990), who showed that patents are not a perfect measure of R&D output but still are a relevant

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proxy for technological dynamics, called for further empirical and theoretical research on patents.

Following the publication of patent datasets by the US Patent and Trademark Office (USPTO) and the OECD and European Patent Office (EPO), several studies have investigated the features of patent documentation, focusing especially on (backward) citations. These empirical studies stress the relevance of geographical and industrial knowledge spillovers,[1] while studies of patent quality depict the heterogeneity—principally in terms of market value—of granted patents.[2] Several studies also analyse patent characteristics such as forward citations, claims and the propensity to apply to the three main patent offices: EPO, JPO and USPTO. Work on patent quality is inconclusive—probably because most is based on estimations that use different survey data (see Van Zeebroeck and van Pottelsberghe de la Potterie 2011).

Recent availability of large, harmonised and updated patent datasets potentially should help to overcome distortions. For instance, the OECD-EPO regional patent dataset (REGPAT) provides a set of variables connected to patent applications—such as typology of backward and forward citations—as well as their direct and indirect linkage to external regional level variables. Among those variables, many refer to the characteristics of R&D and innovation, based on regional data provided by the OECD. In particular, REGPAT includes data on patent inventor(s) and applicant(s) including region of residence which allows micro-matching with OECD variables for regional technology patterns. For example, regional business and government expenditure on R&D or human resources employed in regional high-tech industries.

The available data allow deeper testing of some of the concepts highlighted in the regional systems of innovation framework (Cooke et al. 1997). Although patenting is a core part of most firms' strategies, the role of public institutions and local environment cannot be ignored. We try to highlight the interaction between these variables and patent production to proxy for regional technological advancement and local development more generally.

This chapter is organised as follows: Sect. 10.2 describes the theoretical background to the variables tested in the model; Sect. 10.3 presents the dataset used, describes selection of the variables and discusses the principal descriptive statistics. Section 10.4 presents the methodology and discusses the results. Section 10.5 concludes the chapter.

[1]Among others, Caballero and Jaffe (1993), Henderson et al. (2005), Jaffe et al. (2005) and Schettino (2007).

[2]See Harhoff et al. (1999), Lanjouw and Schankerman (2004) and Hall et al. (2007).

10.2 Theoretical Background

As proposed in the 'regional systems of innovation' perspective (Cooke 1992), institutional factors, such as presence of public research institutes and universities and formal and informal networks of firms and researchers, have been used to explain regional technological development. In this evolutionary framework, it is not only accumulation of certain input factors in a given location (see Krugman and Venables 1996) that leads to economic growth but also technological accumulation at regional level provides specific inputs, such as spin-offs, local labour mobility and social networking (Boschma and Frenken 2009). Technological spillovers help to explain the localisation of innovation activities in a given area (von Hippel 1988; Feldman 1994; Antonelli 2010): firms' technological assets create new technological advantages and help in the absorption of external knowledge (Cohen and Levinthal 1990). Spatial proximity along with maintenance of cumulative relationships between business and public actors (Cooke et al. 1997) also promotes innovation. The presence in regional innovation systems of large corporations and multinationals that engage in R&D activity promotes a polarisation effect: the best actors in the world tend to cluster in so-called 'higher-order regions' (Cantwell and Iammarino 2001).

In order to operationalise these notions, quantitative analyses have used patent counts and/or their distribution (by year, by country or by geographical unit) and determinants. The pioneering results in Hausman et al. (1984, 1986) influenced subsequent research. These authors used firm-level data to investigate the R&D–patents relationship and concluded that the number of patent applications is a function of R&D expenditure. Their approach was adopted by other scholars such as Montalvo (1993), Cincera (1997, 2005), Hall and Ziedonis (2001) and Yueh (2009) who explore this relationship applying more sophisticated econometric tools to different datasets. Their main results substantially confirm the relevant influence of R&D expenditure (current or lagged) on patent applications found by Hausman et al. (1984, 1986).

In line with these approaches, this chapter provides a preliminary assessment of patenting propensity from a regional point of view: the novelty of our investigation lies in the fact that we estimate the R&D-patenting relationship, on the totality of patent applications filed with the EPO in 2000–2010, by the European region[3] of inventors' residence. To construct our panel, we extracted data from the OECD-EPO regional patent dataset (REGPAT)[4] counting number of applications annually[5]

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[3]EU27 + EFTA countries, NUTS 2 level.

[4]OECD-REGPAT database, June 2012—includes patent applications to the EPO (derived from PATSTAT, April 2012) and international PCT (Patent Cooperation Treaty) patents (derived from the OECD patent database, including patents published up to May 2012). Note that the regional breakdown refers to the latest revision to NUTS. The dataset covers regional information for most OECD countries and the EU27, plus the BRICs. We thank Helene Dernis for providing the data.

[5]Fractioned following Narin and Breizman (1995).

by region.[6] We selected our explanatory variables from the EUROSTAT and OECD databases,[7] to estimate the impact of R&D expenditure (at business enterprise and government levels) on investment in high-skilled human capital, employment in high-tech industries and enterprise size on patenting propensity.

10.3 Data and Statistics

The choice of variables for the estimations follows the idea that the link between R&D efforts and patenting propensity should be analysed based on the territory where these efforts are undertaken. As explained in Cozza et al. (2012), EUROSTAT R&D data at regional level reflect the *execution* of R&D in a specific region, no matter who owns the investment. This means that a firm with R&D activities in more than one region in the same country, and multinational firms, contributes to EUROSTAT regional figures proportional to their real investment in the region. In other words, the location of the headquarters has no effect on these data.

The same logic is reflected in our use of patent applications by inventor's region. Although there are some caveats,[8] we catch the connection to the territory where the invention took place. Inventor's region of residence is the best proxy for this—applicant's region of residence would imply a bias towards the location of the firm's headquarters. This choice would then depart from the choice related to R&D data and would distort the analysis.

For example, a firm is headquartered in region X, where it performs R&D for 100 and where 5 of its researchers/inventors are resident. This firm also has R&D activities for 50 in region Y and R&D activities for 30 in region Z, where, respectively, 3 and 2 researchers/inventors are residents. Each researcher is an inventor of a single patent. In our approach, based on the *execution*, the three regions account for 100, 50 and 30 R&D investments, and for 5, 3 and 2 patent applications, respectively. Based on the *ownership* approach, instead, region X would account for 180 R&D investments and 10 patent applications, while regions Y and Z would account for 0. This would misrepresent the real contribution of each territory (region) to technological change.

The other variables were chosen on a similar basis: average size of firms by region was calculated based on number of employees divided by number of local units in the region; the HRST (Human Resources in Science and Technology) variable is based on individuals (graduates and workers) and their region of residence; regional GDP is a regional level variable.

[6]The choice of inventor rather than applicant is discussed in Sect. 10.3.

[7]Selection made at the NUTS 2 level.

[8]We refer to the case of an inventor commuting daily from region of residence to workplace region. This would lose the connection to the territory of the invention (workplace region), overestimating the region of residence only.

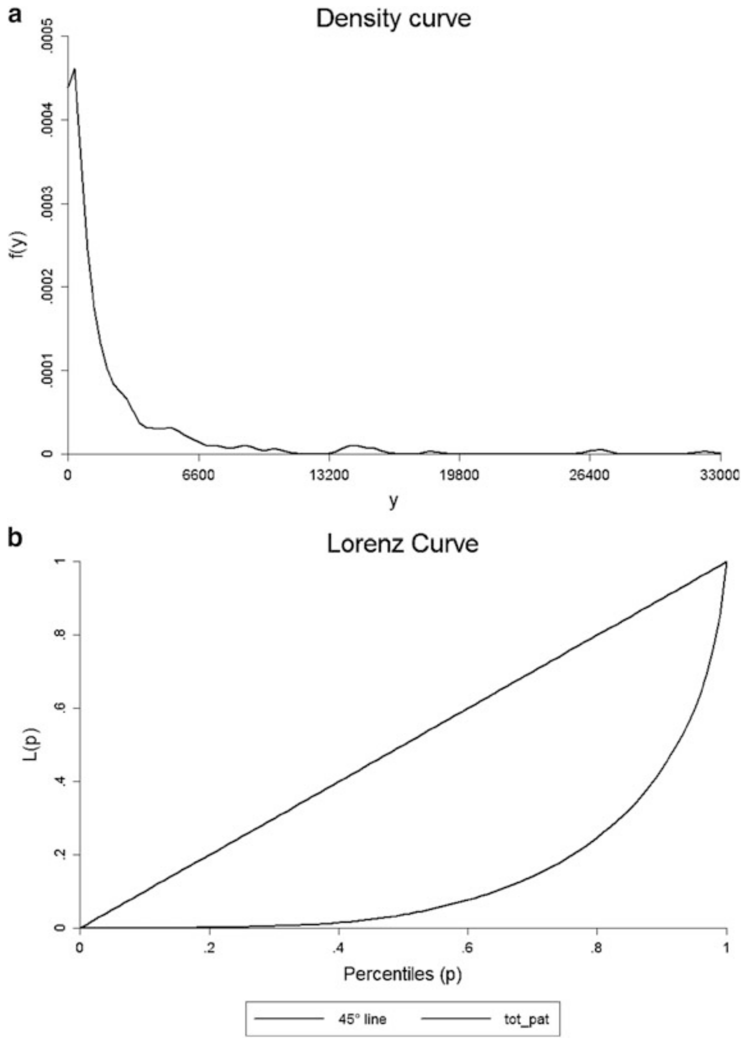

Fig. 10.1 Distribution of total patent applications by region, years 2000–2010 (*Source* Our estimation using OECD-EPO REGPAT data)

Both the REGPAT and OECD regional R&D databases provide an overview of the technological efforts in Europe over a long time span. We use these data to give an idea of the top performing regions and the level of concentration of patent applications and R&D expenditure.

Figure 10.1 depict the uneven distribution of patent applications (2000–2010) by region. Both density and Lorenz curves show a high degree of concentration in the top regions, which is confirmed by the numbers in Table 10.1.

Table 10.1 Total patent applications in top regions, years 1978–2011

Region	Patent application 1978–2011	Cumulated percentage of patent applications 1978–2011 (%)	Ranking 1978–2011	Patent applications 2000–2010	Cumulated percentage of patent applications 2000–2010 (%)	Ranking 2000–2010
Île de France	71.56	6	1	32.152	5	1
Oberbayern	53.514	11	2	26.517	10	3
Stuttgart	48.38	15	3	26.998	14	2
Darmstadt	37.671	18	4	15.606	17	5
Düsseldorf	35.333	21	5	15.338	19	6
Köln	31.878	24	6	14.271	22	9
Noord-Brabant	30.303	26	7	18.446	25	4
Rhône-Alpes	28.721	29	8	14.527	27	8
Lombardia	28.532	31	9	14.544	29	7
Karlsruhe	26.547	33	10	13.943	32	10
Top regions total	392.439			192.342		
Overall total	**1.176.346**			**607.06**		

Source Our estimation using EPO-OECD REGPAT dataset

Figure 10.2 shows that the patent distribution generally follows local GDP levels: in the richest regions (and countries), patenting propensity is higher, indirectly confirming the dual linkage between growth and innovation. From this perspective, Fig. 10.2 shows the significant differences among European countries: number of applications by inventor residents in the eastern regions is much smaller than the number for those residents in western regions. Among these latter, the regions of the so-called *PIIGS* (Portugal, Italy, Ireland, Greece and Spain) countries, and with the exception of the Italian region Lombardia, patenting propensity is lower than in the central and northern European countries (especially those in Germany). It is important to notice that the uneven patent application distribution increased after the 2007 crisis. Since the adoption of new technologies is crucial for income growth and catch up, the absence of strong political measures from local policymakers increases the distance among these groups of European regions.

It is well known [see among others Van Zeebroeck and van Pottelsberghe de la Potterie (2011) and Schettino et al. (2013)] that patents present a significant degree of heterogeneity, and this must be taken into account in the analysis. However, our database has not allowed us to use the variables normally adopted in order to estimate patent values (forward citations, claims, etc.). In any case, a valid proxy for measuring such value is the so-called 'triadic patenting' (see among others van Zeebroeck 2011) that is available in our database. For the purposes of this work, we find that top performing regions in terms of total applications are also those where the majority of triadic patents are filed (see Fig. 10.3).

Figure 10.4 depicts patent concentration by country and respective Gini index. Confirming the picture in Figs. 10.1, 10.2 and 10.3, total patent distribution is very

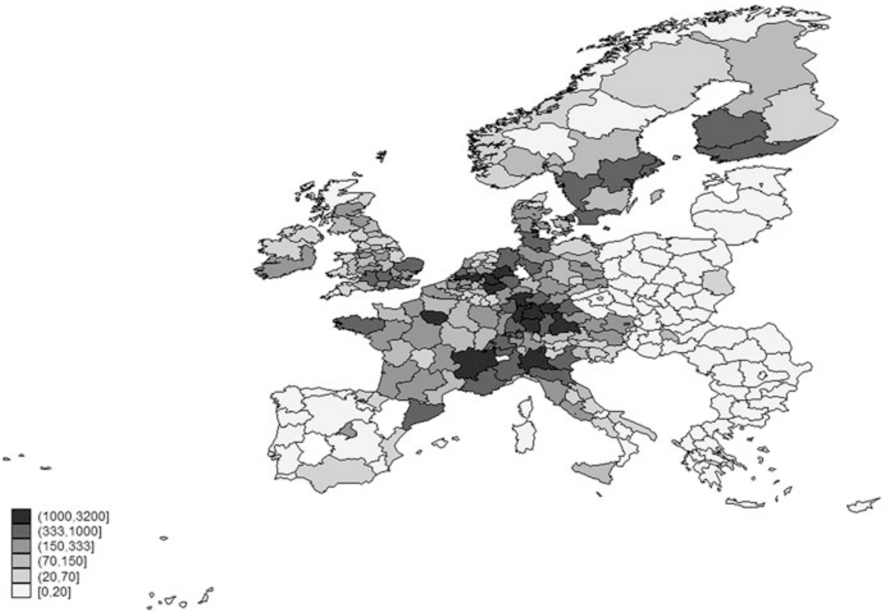

Fig. 10.2 Total patent applications by region, years 2000–2010 (*Source* Our estimation using OECD-EPO REGPAT data)

uneven; the Gini outcome for the whole population is 0.72, a value that is stable along the whole period.[9] In relation to concentration by country, France and Italy show high values: this is due mainly to the relative relevance of the Ile-de-France and Lombardia (and Lazio) regions, whose inventors filed a significant share of total applications in the period (see below for a more detailed explanation). In contrast, the number of applications in three top performing countries, Germany, Great Britain and Switzerland, is not concentrated in a small number of regions, which suggests that, in these countries, the high level of innovation culture is distributed across the whole territory.

Among the top performing regions, notice that the same ones appear in the whole period (1978–2011) and the shorter period (2000–2010) used for the econometric estimations. The majority of inventors are residents in the regions of the most important industrial European cities (e.g. Paris, Munich, Stuttgart, Eindhoven, Milan) and the German regions, which are definitely predominant (six out of the top ten regions). Also, the relative weight of these ten German regions in the total remains stable across the two periods. They account for about one-third of total patent applications (see Table 10.1).

[9]The test performed on Gini2000 and Gini2010 excludes a statistically significant difference between the indexes.

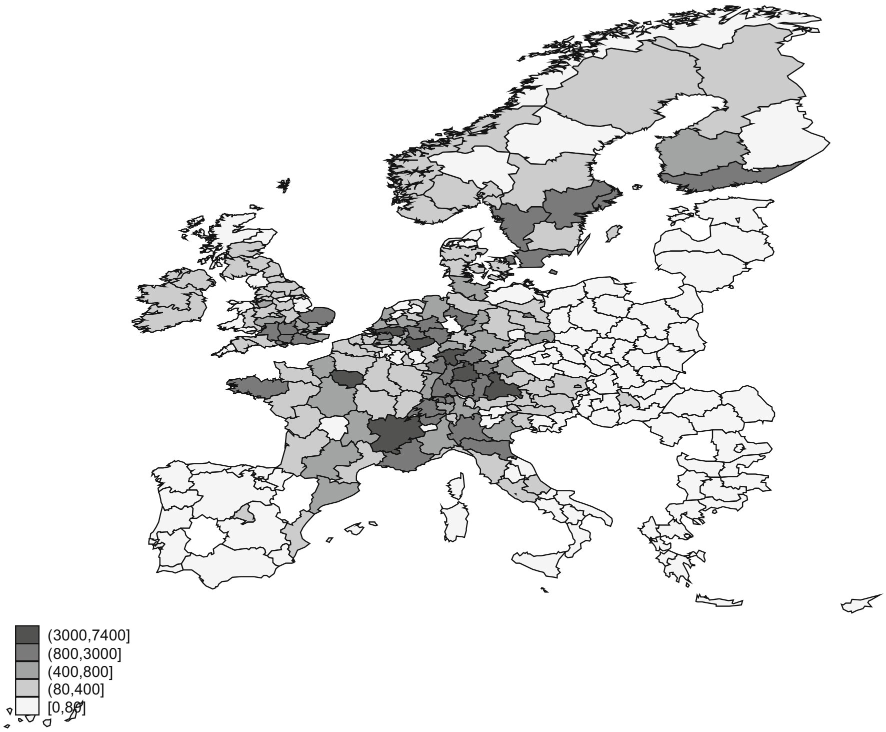

Fig. 10.3 Triadic patents by region, years 2000–2010 (*Source* Our estimation using OECD-EPO REGPAT data)

The same regions emerge when we consider gross investment in R&D. In year 2009, for instance, eight of the above-mentioned regions are also the top performers of R&D with just a few exceptions. Figure 10.5 shows that the composition of gross investment varies across regions, with some strongly reliant on business expenditure (e.g. Stuttgart), some reliant on higher education expenditure (e.g. Inner London) and some others on government expenditure (e.g. Madrid and Köln).

On the same basis, R&D expenditure concentration by region appears similar to the pattern for patent applications. Figures 10.6 and 10.7 depict a European area characterised by high levels of R&D expenditure (business and total) in the central-western regions, i.e. in the richer countries, with a very unsatisfactory situation in the eastern and *PIIGS* regions.

The technological development of regions is, of course, dependent on several other motivations. These include their industrial structure (presence of large companies, clusters, infrastructures, etc.) as well as their different historical, social and regional patterns of development. Such features are often reflected by the regional human capital variables. For instance, a high degree of employees in high-tech industries is a proxy for a technologically advanced business structure. Similarly,

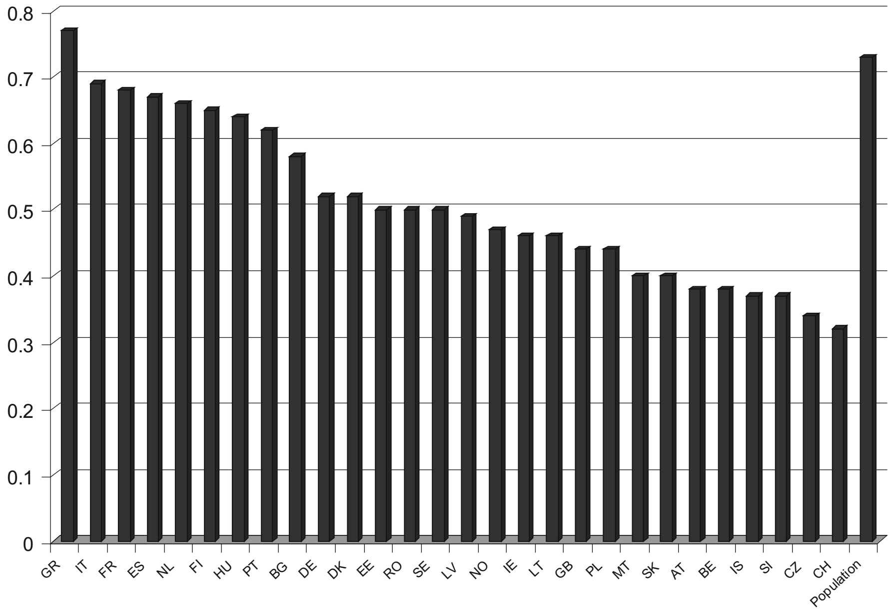

Fig. 10.4 Gini index by country—total patent applications, years 2000–2010 (*Source* Our estimation using OECD-EPO REGPAT data)

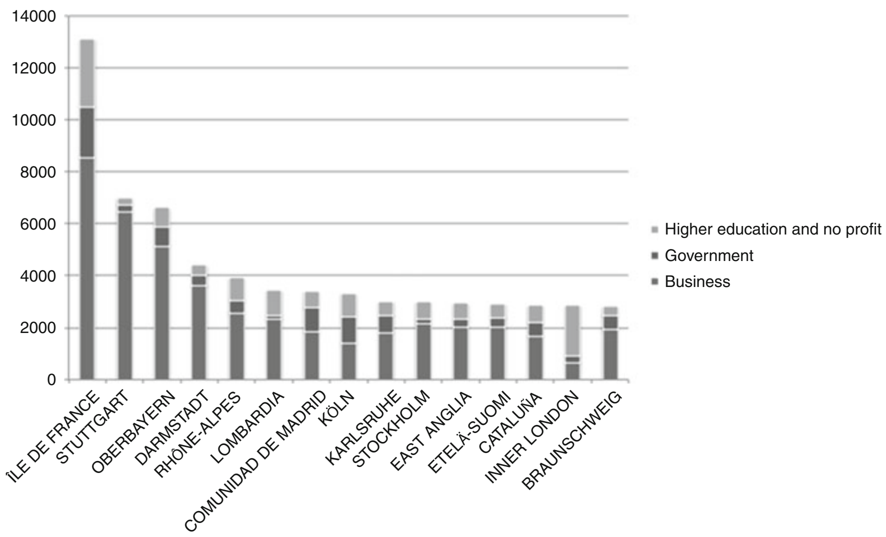

Fig. 10.5 Gross Investment in R&D in top performing regions, in 2000pps, year 2009, by sector of performance (*Source* Our estimation using EUROSTAT/OECD data)

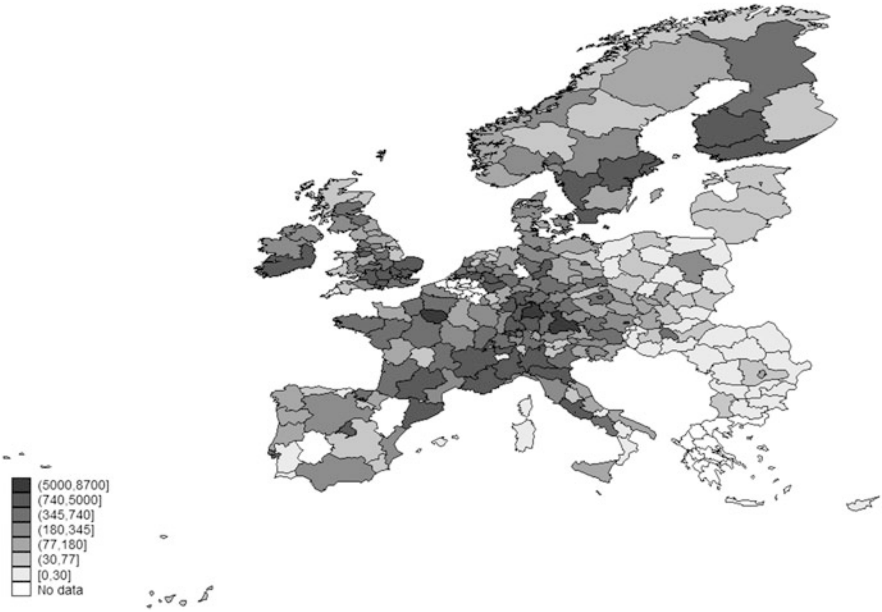

Fig. 10.6 Average Business Enterprises' R&D expenditure (BERD) by region, years 2000–2009 (*Source* Our estimation using EUROSTAT/OECD data)

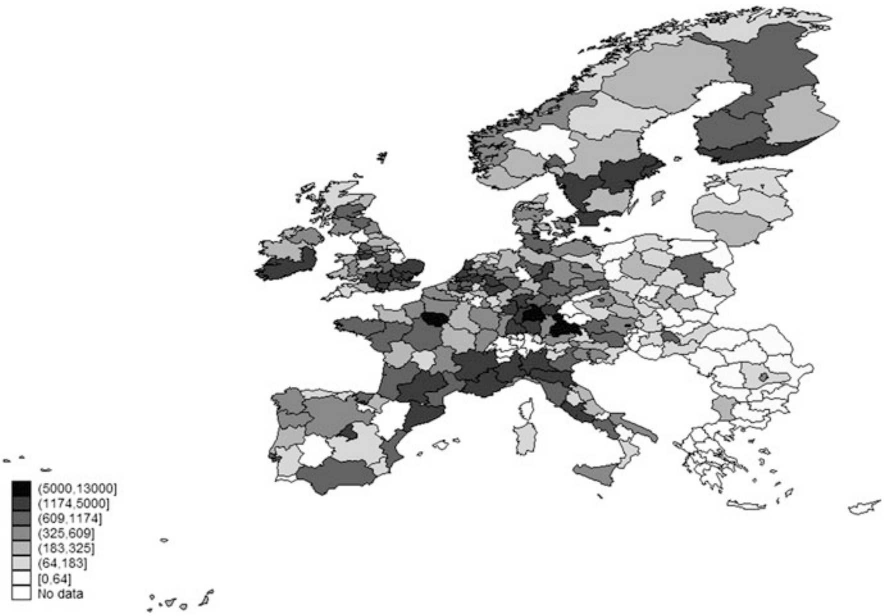

Fig. 10.7 Average gross R&D expenditure (GERD) by region, years 2000–2009 (*Source* Our estimation using EUROSTAT/OECD data)

Table 10.2 High-tech employment and human resource in science and technology by region (average 2000–2010)

Top regions	Htec_emp	Top regions	Hrst
Stuttgart	20.4	Île de France	3,370.64
Braunschweig	18.13	Comunidad de Madrid	1,628.55
Tübingen	16.95	Lombardia	1,599.55
Karlsruhe	16.34	Cataluña	1,409.09
Kozep-Dunantul	15.13	Rhône-Alpes	1,246.73
Niederbayern	14.67	Andalucía	1,241.36
Rheinhessen-Pfalz	14.4	*Oberbayern*	1,199.27
Freiburg	14.38	Outer London	1,145.73
Oberpfalz	14.08	Düsseldorf	1,125.36
Unterfranken	14.05	Berlin	1,044
Schwaben	13.51	Köln	1,028.64
Franche-Comté	13.24	Mazowieckie	1,007.64
Nyugat-Dunantul	13.06	*Stuttgart*	1,006
Oberbayern	12.99	Darmstadt	993.82
Severovychod	12.91	Inner London	976.27
Mittelfranken	12.8	Lazio	950.91
Piemonte	12.13	Zuid-Holland	913.64
Zapadne Slovensko	11.67	Provence-Alpes-Côte D'azur	885.27
Kassel	11.62	Comunidad Valenciana	842.73
Jihozapad	11.57	Noord-Holland	785.64

Source Our estimation using EUROSTAT/OECD data

the amount of human resources in science and technology reflects the involvement of regions in high value-added activities.

These two variables should not be considered as alternatives: a region characterised by many high-tech companies and employees might well be lagging behind in terms of workers in science and technology occupations as a whole. In fact, as shown in Table 10.2, only 2 regions are among the top 21 in both indicators, over the considered period. As we can see in the table, top regions in terms of *Htec_emp* are also those with a higher number of patent applications (see previous Figures); on the other side, the patenting performance of top regions in *Hrst* appears to be lower. While the former variable reflects only the business involvement in R&D, the latter includes public efforts that are less correlated with patenting activity. In fact, public R&D is often basic research oriented and devoted more to social outcomes than to the commercial exploitation of inventions.

The most innovative countries also show high degrees of internal variability. Figure 10.8 highlights that the top patent application countries in the period 2000–2010 (e.g. France, Germany and the Netherlands) show wide internal differences between their respective top and least performing regions. For instance, values for Germany range from 26,998 in the Stuttgart region to 532 in Trier. Of course, these values incorporate differences in regional size (area) and population. Therefore, in

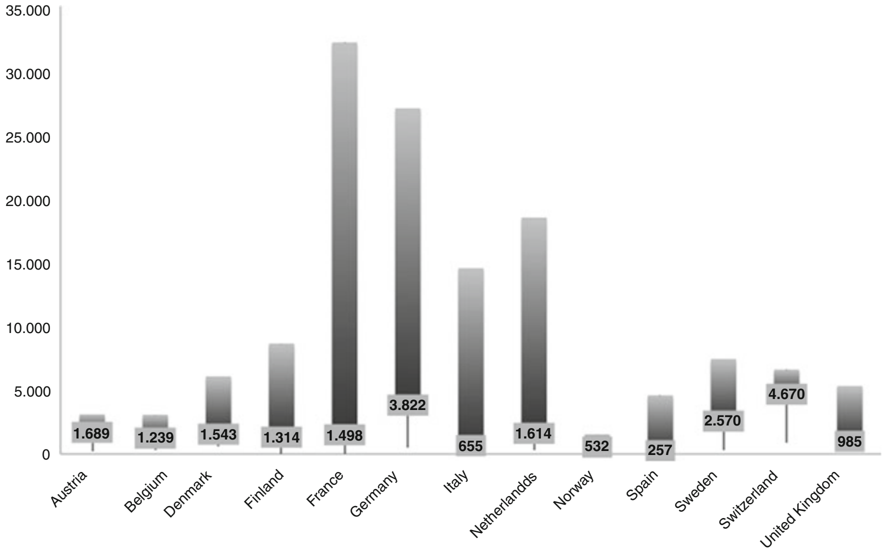

Fig. 10.8 Total patent applications in top and least region and median in each country, years 2000–2010 (*Source* Our estimation using EPO-OECD REGPAT dataset)

Fig. 10.8, we add the median value, in order to distinguish between two groups of countries: those whose regions show high levels of patenting and which are all close to the country median (e.g. Switzerland and Sweden) and those whose median value is far below the top value. Within this second group, the case of Italy is particularly significant: it is ranked fourth for regional value (14,544 in Lombardia), but it also includes a region with the lowest number of patent applications (Molise, 17) and one of the lowest median values.

10.4 Methodology and Results

Section 10.3 presented the principal features of our dataset. As already mentioned, lack of data for a significant number of regions between 1978 and 1999 means our empirical analysis is based on the period 2000–2010. This choice can be justified from a theoretical point of view by the fact that many European countries changed their intellectual property rights structures after the collapse of the USSR; this long process began around 1990 and did not stabilise for at least 10 years. From an empirical point of view, in the years before 2000, for many of our independent variables we encountered a so-called ‘excess zero’ problem (see also Yueh 2009). In order to limit the correlated regression bias, we base our estimations on data for

2000–2010. Thus, our unbalanced panel dataset is composed of 3,209 observations, i.e. fewer than 300 observations per year.[10]

It is well known that the discrete, non-negative nature of patent data (count data) makes the usual linear regression models inappropriate. However, Hausman et al. (1986) suggest using a Poisson process in order to describe events that occur independently and randomly in time, as is the case for patents. Thus, in line with Cincera (1997, 2005) and Yueh (2009), we adopt two distinct models—Negative Binomial and Poisson—in order to estimate the regional patent propensity function, relying on the following determinants:

1. Private/Business R&D expenditure (*Berd*[11]);
2. Government R&D expenditure (as a fraction of local GDP) (*Goverd_gdp*);
3. Share of human resources employed in high-tech industries (*Htec_emp*);
4. The number of highly qualified and/or workers in science and technology occupations (*Hrst*);
5. Average enterprise size (*Ent_size*).

Use of R&D without lagged time follows Hall and Ziedonis (2001) and is justified by the persistent nature of R&D. It is unlikely that a firm undertaking a certain amount of R&D in year $t-2$ (or $t-4$ in e.g. science-based sectors, where results take more time) and applying for patents in year t will reduce their level of R&D in the year t.

We use the variable *Goverd* as a share of GDP: (1) in order to remove hypothetical collinearity with other variables (especially *Berd*); (2) in order to eliminate possible related 'regional bias'. In the case of France or Italy, for instance, the highest share of R&D spending by public research institutions, such as CNRS or CNR, is in the region of the capital city—this is despite both institutions having R&D activities across their national territories. Therefore, use of this variable as a share of GDP reduces the distance of these two regions from the rest of these countries. In other countries (e.g. Germany or Switzerland), the bias is not so strong.

The variable *Ent_size* is computed as the number of employees in the region divided by the number of local units in the region. This reflects the average size of local regional units (laboratories, plants, offices, etc.), not firms. In other words, this 'size' is not excessively influenced by the presence of large firms, especially those with many branches widespread in the national territory or abroad.

Before performing our econometric exercise, we control for the existence of spatial correlation in terms of the dependent variable excluding that regional

[10]The number of observations fluctuates across the years (282–300) because although the number of regions per country is generally constant over time, the regional structures of eastern European countries have changed in recent years.

[11]Both BERD and GOVERD have been calculated in PPS, 2,000 prices.

Table 10.3 Hausman test output

	Negative binomial	Poisson
Test: Ho: difference in coefficients not systematic		
$chi^2 = (b - B)'[(V\_b - V\_B)\hat{}(-1)]\ (b - B)$	18.61***	119.19***
$Prob > chi^2$	0.0023	0

Source Our estimations on REGPAT and OECD datasets
*,**,*** <0.1, <0.05, <0.01 confidence level

proximity could generate correlation bias in patent applications by inventor.[12] To increase the robustness of our estimations, given that the variables included in the model might potentially be endogenous, we also applied a GMM model. Thus, we opted for a standard dynamic patent applications equation with a 3-year lagged dependent variable, and estimation of our dynamic panel by means of Arellano and Bond's (1991) GMM.[13]

When performing panel analysis, the first problem is the choice of the random/fixed effect estimation; the literature shows that when firm- or region-specific effects are correlated with some explanatory variables, the random effects model is not consistent. In particular, Cincera (1997) shows that, in the R&D–patents relationship, the correlation between dependent and independent variables is significant and a random effects specification could give an upwardly biased estimate. This intuition has been confirmed by a Hausman test conducted on each model: Table 10.3 shows that fixed effect is the best specification.

Table 10.4 shows results that are substantially consistent with Cincera (2005) and Yueh (2009). The coefficients of the variables related to human capital are significant in each model meaning that investment in highly qualified human capital (*Hrst*) and level of employment in high-tech industries (*Htec_emp*) increase the propensity for patenting at the EPO. In relation to R&D expenditure, *Berd* has a positive and strong impact on the dependent variable; it means (for the NBM) that 1,000 € of business investment in R&D leads, on average, to one patent application. Government expenditure on R&D has a significant role in the NBM but is not significant in the PM and GMM models. However, the positive outcome for NBM suggests that a higher share of regional GDP spent on public R&D increases both the patenting propensity of local public researchers and also, because of regional knowledge spillovers, that of private researchers.[14]

Finally, enterprise size (*Ent_size*) is not significant in the NBM; it has a weak negative impact in the PM, and in the GMM model has a positive coefficient which is significant only at 10 %. The inconsistency in this result for 'size' can be explained

[12]We apply Moran's test to the whole sample (2000–2010) and to 1 year (2008). In both cases, the test confirms that we can accept the null hypothesis that there is zero spatial autocorrelation present in the variable considered (Moran I (2000–2010) = 0.011; Moran I (2008) = 0.004).

[13]GMM estimations were performed by using the *xtabond2* for Stata 10 (see also Roodman 2006).

[14]See Hall et al. (2003).

Table 10.4 Regressions results

	Negative binomial (NBM)	Poisson (PM)	GMM (A/B)[a]
Dependent variable			
Patent application by inventor (2000–2010)	Coefficients	Coefficients	Coefficients
Determinants			
Hrst	0.0006***	0.0004***	0.197***
Htec_emp	0.014***	0.011***	5.72***
Ent_size	−0.00007	−0.0001**	1.282*
Berd	0.0001***	0.00004***	0.036***
Goverd_gdp	0.26***	0.033	−8.205
Constant	3.44***		
Number of obs	1,257	1,257	590
Number of groups	209	209	146
Wald chi^2	248.68	400.01	63.13
Prob > chi^2	0	0	0
N instruments			233
Arellano–Bond test for AR(1)			Pr > z = 0.005
Arellano–Bond test for AR(2)			Pr > z = 0.623
Hansen test of overid. restrictions			Prob > chi^2 = 0.998

Source Our estimations based on REGPAT and OECD datasets
[a]Three-year lagged dependent variables are not significantly different from zero; Instruments for first differences equation GMM-type: L(1/.). (L.tot_applic L2.tot_applic L3.tot_applic hrst htec_emp ent_size berd goverd_gdp)
*, **, *** <0.1, <0.05, <0.01 confidence level, respectively

by the way the variable was constructed, as described above. For instance, a large firm with 1,000 employees in the country spread over 10 regions in 10 local units (plants or laboratories), accounts in each region as if it was a medium-sized firm with 100 employees. As a consequence, at regional level, the R&D spending of this medium firm has the same ‘weight’ as that of 1 of the 10 local units of the large firm. Therefore, a ‘small-firm-sized’ region can be either a region with only small firms or a region with small firms and local branches of large firms. This explains the counterintuitive behaviour of the size variable in our models.

10.5 Concluding Remarks

This chapter studied the patenting propensity at the European regional level, using the REGPAT dataset for patents and EUROSTAT-OECD databases for the explanatory variables. Descriptive and econometric results confirm two main issues:

– Both R&D performance and patenting are strongly concentrated in some European regions, mainly within central and northern countries.

– R&D spending, and particularly private investment, has a positive and strong impact on patenting propensity.

This uneven distribution suggests that local policymakers, especially in eastern and southern countries, should take strong policy measures to reduce the distance with the leading European countries. These measures could include direct and indirect support for innovation such as:

– Increase in overall government expenditure on R&D;
– Incentives (e.g. tax credits) to increase private expenditure on R&D;
– Support for high-tech departments in public research centres and universities;
– Promotion of science and technology employment.

This chapter also contributes through its use of variables representing direct linkages to the territory, that is, the regions where the R&D is performed, whether by a local firm or the subsidiary of a large/multinational firm, and region of residence of inventors rather than patent applicants. The correlation between in-house R&D and patent applications in regions where large companies have their headquarters is rather obvious; the results of our analysis highlight a relation between R&D spending (as well as investments in highly qualified human capital) and patenting propensity in the territory. The reasons for this relation might be that:

1. Many different innovation players (large firms, innovative small- and medium-sized enterprises—SMEs, multinational corporations, public research centres) belong to the identified top regions, which can be classified as regional innovation systems (see, among others, Cooke et al. 1997);
2. The *execution* of R&D and patenting are centralised in the top performing regions, where *execution* and patent *ownership* coincide, close to the headquarters of top global players (see Patel and Pavitt 1991).

In our model, both explanations are confirmed by the counterintuitive behaviour of enterprise size, which shows inconsistent behaviour in the estimated models. In order to increase patenting propensity, it is not important for the region to host large companies; the main driver appears to be innovation distributed across the territory. However, it is unclear whether this distributed innovation relates to many independent SMEs or of subsidiaries and branches of large firms resident in the region or elsewhere. The fact that the main regions, according to our descriptive statistics, are those where large firms and multinationals are headquartered suggests that patent *ownership* might still play a crucial role in both performance of R&D and patenting. Further research is needed to confirm this.

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Chapter 11
Family Origin and Early School Leaving in Italy: The Long-Term Effects of Internal Migration

Carmen Aina, Giorgia Casalone, and Paolo Ghinetti

Abstract The proportion of early school leavers in Italy is high by European Union standards. However, it is not uniformly distributed across the country: in Southern regions, it is almost double than in Centre-Northern area. This chapter goes beyond descriptive evidence and examines the conditional probability of leaving school with (at most) the compulsory schooling certificate in Italy using seven waves of Bank of Italy's SHIW data, covering individuals born in the period from 1979 to 1995. Among various determinants, we focus on the role played by family origin. Our results show that youths born in the Centre-North with both parents from Southern Italy (second generation internal migrants) behave similarly to youths born and living in the South, so that they are more likely to drop out school earlier than comparable individuals born in the Centre-North with parents from the same area (natives). When only the household head is from the South, second generation migrants are similar to natives and the assimilation with native born in terms of schooling choices at the age of 14 is complete. Differences in family characteristics (education, financial conditions) are able to account for a large share of raw differences in education decisions between individuals born in Centre-North vs. South, as well as between natives and second generation migrants born in the Centre-North of Italy. The analysis of these dynamics over time shows that differences across groups of youths defined by their origin narrow since the mid-2000.

Keywords Internal migration • Education

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11.1 Introduction

Three important characteristics of the Italian society are the persistently high rates of early school leavers, the impressive youth unemployment rates and the massive migration flows from the poorer Southern regions to the richer Northern ones occurred in the last century.

In Italy schooling drop-out rates are substantially higher than in many other countries at any educational level. Even among young generations, there is still a relatively high fraction of population who do not continue after compulsory schooling or who leave education during the secondary cycle. According to Eurostat (2012), Italy ranks third (after Portugal and Spain) among European Union Countries in terms of early school leavers share (Table 11.1).[1] Notwithstanding the remarkable reduction occurred in the last 10 years, one-fifth of the Italian young people in the 18–24 age class drop education after having obtained the compulsory schooling certificate. The distribution of early school leavers in Italy, however, is not homogeneous within the country. By using the definition of Eurostat, the percentage of early school leavers in Centre-Northern Italy is about 16.6 %—not far from the average European Union percentage—whereas in Southern regions, it is 25 % (Bank of Italy 2010).

Educational gaps among youths living in different Italian regions are therefore noteworthy even in terms of raw educational attainment rates.[2] The reasons behind the higher proportion of early school leavers in Southern Italy may be numerous, ranging from more binding income constraints and poorer parental backgrounds to lower returns to education.

Table 11.1 Percentage of early school leavers in Europe

	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Finland	7.9	9.9	9	9.5	9.7	10.1	10	10.3	9.7	9.1	9.8	9.9	10.3
France	14.9	14.7	13.3	13.5	13.4	13.2	12.8	12.2	12.4	12.6	11.8	12.2	12.6
Germany	–	14.9	14.6	12.3	12.5	12.8	12.1	13.5	13.6	12.5	11.8	11.1	11.9
Italy	28.4	27.2	25.1	25.9	24.2	23	22.3	22	20.6	19.7	19.7	19.2	18.8
Norway	–	–	12.9	8.9	13.5	6.3	4.7	4.6	17.8	18.4	17	17.6	17.4
Portugal	40.6	46.6	44.9	43.6	44.2	45	41.2	39.4	38.8	39.1	36.9	31.2	28.7
Spain	29.6	29.5	29.1	29.7	30.7	31.6	32	30.8	30.5	31	31.9	31.2	28.4
Sweden	–	6.9	7.3	10.2	10	9.2	9.2	10.8	12.4	11.4	11.1	7	6.4
United Kingdom	–	19.8	18.2	17.8	17.6	12.1	12.1	11.6	11.3	16.6	17	15.7	14.9
EU (27)	–	–	17.6	17.2	17	16.6	16.1	15.8	15.5	15.1	14.9	14.4	14.1

Source Eurostat (2012)

[1] The rate of early school leavers is defined as the proportion of the population aged 18–24 with only lower secondary education or less and no longer in education or training.

[2] PISA surveys emphasise youths' educational gaps amongst Northern and Southern Italy also in terms of skills acquired.

As regards internal migration flows, they have been very large especially during the 1960s and the 1970s and have regarded especially individuals with poor economic and cultural background.[3] They were declining during the 1990s and have reached new impulse in recent years. However, internal migration is now more concentrated on high-skilled individuals (see Mocetti and Porello 2010).

Migration and early school drop out have non-negligible consequences for individuals. On the one hand, early school leavers are more exposed to a number of economic risks affecting individual well-being over the life cycle, such as unemployment, low wages, black work, poor health and so on.

On the other hand, the movement of individuals and families from a poor region to a new and generally more developed one may be associated with a number of assimilation and integration problems in the destination area, especially if the background of the migrant is poor. Moreover, the literature shows that a complete economic and social integration may be very lengthy, so that the consequences of migration are persistent and spread not only on the generation of the migrant but also on the subsequent one, the so-called second generation migrants. Given the Italian internal migration patterns, the bulk of them are the individuals born in Northern regions from the beginning of the 1970s up to the beginning of the 1980s from parents with a Southern origin.

For them, on the one hand education is the main opportunity of social and cultural integration in the residence area. On the other hand, they may be more at risk of withdrawal because of their recent family history of migration.

The aim of this chapter is to assess whether there is a long-term effect of internal migration in Italy and, in particular, whether second generation migrants face a different early school-leaving probability than same age individuals born in families of natives. If returns to education play a role in affecting the decision on the amount of education to achieve, we would expect that, once controlled for family background and financial resources, people who share the same labour market environment would reach the same educational level, independently from the origin of their family.

The main econometric results suggest that youths who have only one parent (generally the father) from Southern Italy do not experience a different behaviour in terms of education decisions after compulsory schooling with respect to their Centre-North native-born peers. According to our estimates, their assimilation in the area of residence can be considered complete, at least with respect to the educational outcome analysed. A different result arises for children with two parents who moved from the South, as they are more likely to leave early education. Overall estimates show that females' educational decisions are more shaped by the household context, as they suffer greatly not only from their parents' migration status but also from poor family financial conditions and from the presence of siblings. Finally, a progressive homogenisation in terms of education decisions after compulsory schooling across individuals of diverse origin or living in different areas of the country seems to

[3] See the appendix for a brief overview of Italian internal migration.

emerge over the last years, once differences in family background and financial condition are controlled for.

11.2 Literature Review

High early school drop-out rates have several consequences, e.g. high unemployment rates, low wages, poor health and high risk of exclusion from society at large.

Although there is rise over time in the proportion of children staying on at school after the minimum leaving age (see Boeri 2000), differences between individuals from diverse backgrounds are still not negligible. In fact, those who are living in families with poor parental education or financial conditions are more likely to withdraw after compulsory schooling. In order to improve the knowledge about the mechanism of school-leaving choice, several articles explore the links between early school drop out and family background, income and individual ability. Well-established results highlight the positive effects of parental education, social class and number of siblings on the propensity of staying on at school, even when ability and school type are controlled for (Micklewright 1989). Adopting a different perspective, Bratti (2007) explores this phenomenon considering the role played by parental income using the 1970 British Cohort Study in England and Wales. He finds a negative impact of family financial conditions on a child's school drop-out probability at age 16, but quite small. On the contrary, the estimates confirm that what it matters more are the family non-pecuniary factors, more than any other aspects.

Eckstein and Wolpin (1999) examine attendance and work decisions of the US high school students. They highlight that students who drop out have different traits[4] than those who graduate, while being a working student reduces the probability of obtaining the diploma. Oreopoulos (2003) then investigates whether early school leaving is suboptimal, and to do so, he takes into direct account the changes in minimum school-leaving laws in the UK. He finds that the introduction of this law increased by 12 % earnings of individuals who benefited from this intervention, improved their health and happiness, reduced the probability of being in a low-skilled job and unemployed too.

Using matching techniques, Dearden et al. (2005) investigate whether or not schooling subsidy programmes play a positive effect on school participation in UK. They demonstrate that a conditional payment to 16- and 17-year-old contributes to a reduction of drop-out rates within post-compulsory schooling, even if they are not able to ascertain whether or not their result is driven by family liquidity constraints.

An additional explanation of the early drop outs at 16 is provided by the trend of unemployment rates over time. Unemployment may drive poor youth educational outcomes in several ways. In principle, high unemployment may increase individual

[4]When they talk about traits, they refer to abilities, preferences and expectations.

uncertainty about the level of returns to education. However, international empirical evidence on the relation between unemployment and schooling decision does not always support this theoretical prediction, and most studies find a positive effect of unemployment on schooling/enrolment rates, especially for males (Pissarides 1981; Rice 1999; Bozick 2009; Clark 2009). A negative correlation, instead, has been found by Micklewright (1989) and Pastore (2012). Conversely, in a country characterised by persistently high unemployment rates, such as Spain, estimates show no effect of labour market conditions on youth's decision to drop out from school (Petrongolo and San-Segundo 2002). According to Casarico et al. (2011), female university enrollment in Europe is positively related to the probability of employment of mothers residing in the same region. Estimates then suggest that the relation between labour market conditions and educational attainments depends on student's characteristics (for instance, gender but also parental background) and on unemployment itself.

Despite the great attention devoted to these issues at international level, as far as we know, the empirical evidence on early school leavers is very limited for the Italian case.[5]

The attempt of this chapter is hence to fill this void for Italy, considering the high incidence of this phenomenon in this country. Apart from controlling for parental background and labour market conditions, we focus on the role played by being a second generation internal migrant, i.e. a person born in the Centre-Northern Italy but with a Southern origin, in order to disentangle the choices in educational attainments according to the migration status, everything else equal. The inclusion of the latest controls is motivated by the empirical results found in previous studies of a different educational accumulation process for natives and non-natives. Especially, the latter are less likely to stay on at school (Borjas 1994; Dustmann et al. 2005).

11.3 Data and Descriptive Statistics

The ideal dataset to analyse the determinants of school drop-out decisions would be a cohort study of young individuals, tracking their school career as well as their family and personal characteristics. Unfortunately, such data are not available for Italy. Instead, we use the last seven cross sections (1998–2000–2002–2004–2006–2008–2010) of the Bank of Italy Survey of Household Income and Wealth (SHIW), restricting the sample to youths, defined as individuals aged 15–25 and

[5]Baici et al. (2007) analyse early drop out from high school using a cohorts of youth living in the province of Novara. Their main finding is that family background—and in particular parental education—is a decisive factor in the educational failure of youngsters. Aina et al. (2013) use the same dataset to provide evidence of the effect of migration status on youth's educational achievement in a province traditionally characterised by a remarkable migration inflow. Findings show that non-natives, especially male, are more likely to study less.

living with their parents when interviewed. Unlike a cohort study, we then consider 12-year time window to select the individuals of interest. Since the Survey is carried out on the Italian population, data pooling is the natural way to obtain enough observations. Overall, youths included in the analysis were born in the period 1979–1995.[6] Notwithstanding this wide time span, all individuals were subjected to the same compulsory schooling age (from 6 to 14 years of age).

We define early school leavers as those individuals in the class age 15–25 who achieved at most the lower secondary school degree and who are no more in education at the time of the interview. Since our sample is not a panel, we cannot track the entire educational path of individuals and, consequently, we cannot exclude that some of them have attended upper secondary school for some years without achieving the final degree. Anyway, independently from their attempts to pursue education after lower secondary school, early school leavers enter the labour market with—at most—the compulsory schooling degree (from 6 up to 14 years of age).

As for migration, we define it as the movement from the (poorest) Southern regions (Abruzzo, Molise, Campania, Puglia, Basilicata, Calabria, Sicily and Sardinia) to the (richest) Centre-North regions (the remaining Italian regions). We exclude from the sample youths born in Southern Italy and living in Centre-Northern regions (1st generation migrants). Since we do not know the age of migration, we cannot establish for them whether they attended school in the region of origin or in the area of current residence (or in both areas). Therefore, we focus only on the migrants' offspring, namely on children living and born in Centre-Northern regions from parents of Southern origins.

One complication in the definition of the migration status is that individuals can potentially have either one or two parents born in the South. Further, who actually is the parent with Southern origins—whether he/she is the household head or not—can in principle make a difference. In this respect, the existing literature offers a limited guidance: some studies define migration in terms of the household head's (mainly the father) origin, others suggest that having only one non-native parent is not sufficient for being considered a second generation migrant, so that having both parents from Southern regions is required.

Our approach is rather pragmatic; in the empirical analysis, we alternatively use two characterizations of the children's migration status. First, according to a less restrictive interpretation, we define migration in terms of the origin of the household head; migrants' youths are those who born in Centre-Northern regions and live in a family where the household head (father or mother) is born in the South. Accordingly, native offspring are those who live in the Centre-North in families where the household's head is born in the same geographical area. Implicitly, we

[6]In principle, the definition of youth as individuals aged 15–25 at the time of each survey would imply the inclusion of all the cohorts born in the 1973–1995 period. However, we exclude the first five cohorts since an important covariate used in the empirical analysis, namely the gender-specific regional unemployment rate, at the time at which the education decision of dropping out after compulsory schooling—i.e. at the age of 14—is available only since 1993 (1979 + 14).

are then assuming that the origin of the household head is the main determinant of the children migration status.

Second, we also use a more restrictive characterization where the 'pure' migrants are youths living in a household where both the household head (father or mother) and her/his spouse are native of Southern regions; the natives are defined in a similar fashion—both the household head and his/her spouse are born in the Centre-North of Italy. Using this definition, there is also an additional category which includes the youths with a 'mixed' parental background, i.e. children born and living in Centre-North from parents of different origin (one from the South, one from the Centre-North, no matter if he or she is the household head or not).

As a result, individuals are classified into either three or four groups: one is the reference and includes youths born in the South.[7] If the individual is born and living in the Centre-North, his/her status depends on how the migrants are defined. Using the first characterization, the two groups are the natives and (second generation) migrants' offspring; according to the second one, there are three groups: natives (second generation), 'pure' migrants' offspring and the residual mixed category. By definition, all individuals living in the same area have carried out their educational path in the area of residence.

We then follow Micklewright (1989) to formalise the role of parental background by including controls for parents' education (above/below compulsory schooling). Since early school leaving may also be the result of binding economic constraints, we also include indicators of the financial situation of the family, such as house ownership and family log income (normalised by the number of household members).[8]

The final sample is composed of 11,458 observations: 53 % live in Centre-Northern regions and 47 % in Southern Italy. Table 11.2 provides descriptive statistics separately by youths' origin. Column (6) includes the reference category, i.e. those who are born and living in the South. The other columns include youths born in Centre-North. In columns (1) and (2), we separated individuals according to the origin of their household head (less restrictive definition of being a second generation migrant and a native born). In columns (3), (4) and (5), they are divided according to the origin of both the household heads and their spouses (the more restrictive definition). Reported statistics are obtained by applying the weights calculated by Bank of Italy in order to make the selected sample representative of the whole population.

[7]Since internal migration is mainly from the South to the Centre-North, youths born in the South have for the most part both parents from the same area. However, in order to improve the interpretation of our results in both cases, we have dropped the residual group of individuals living in the South but born elsewhere or from parents of different origins (one of the Centre-North and the other from the South).

[8]Including parents' employment status proxies in the estimates does not improve the results, as the corresponding coefficients are never statistically significant. This result is not surprising as parents' education and households' financial resources generally capture the whole effect of the family background.

Table 11.2 Descriptive statistics

	Youths born and living in Centre-North					Youths born and living in the South
	Migration status based on household head origin		Migrat. based on both househ. head and spouse orig			
	(1) HH born in Centre-North: 'natives'	(2) HH born in the South: '2nd generat. migr.'	(3) HH and spouse born in Centre-North: 'pure natives'	(4) HH and spouse born in the South: 'pure 2nd generat. migr.'	(5) HH and spouse born in different areas: 'mixed origin'	(6) All
Obs	5,252	840	4,880	442	770	5,366
Obs (% points)	0.458	0.073	0.426	0.039	0.067	0.468
Females	0.456	0.457	0.458	0.457	0.448	0.476
Mother and father education						
Father primary school	0.121	0.182	0.120	0.238	0.127	0.231
Father lower secondary	0.374	0.464	0.370	0.425	0.462	0.434
Father vocat/upper secondary	0.386	0.260	0.389	0.276	0.288	0.255
Father university degree	0.119	0.094	0.120	0.061	0.122	0.080
Mother primary school	0.106	0.189	0.102	0.235	0.152	0.315
Mother lower secondary	0.387	0.470	0.382	0.532	0.426	0.357
Mother vocat/upper secondary	0.398	0.251	0.409	0.176	0.299	0.264
Mother university degree	0.109	0.089	0.108	0.057	0.123	0.063
House and income						
Number of children	1.917	1.958	1.912	1.934	1.987	2.376
Family-owned house	0.814	0.714	0.819	0.717	0.727	0.695
Equivalent income	26,595	22,527	26,798	21,728	23,664	14,652
Early school leavers	0.094	0.151	0.093	0.181	0.113	0.224

According to the first definition of migration [columns (1) and (2)], migrants' offspring represent the 7.3 % of the overall sample—and the 14 % of the youths living in Centre-Northern regions. Using the stricter definition [columns (3)–(5)], their percentage drops to 3.9 %, lower than that of youths with a mixed family background (about 7 %). Females represent in all groups less than 50 % of the samples. Since we are considering only children living with parents, we miss those (mostly females) who have created their own family. About family background characteristics, migrants have less-educated parents than native born, on average. The average educational level of parents living in Southern regions does not remarkably differ from those who moved to Centre-Northern Italy. This evidence suggests that, at least for the generation of individuals who migrated by 1995, there is no clear selection process based on the parental schooling level.

Besides parental education, also households' economic resources are potential determinants of children's investment in education. One measure of financial resources at the household level is the equivalent income, which is unsurprisingly always greater in Centre-Northern regions. Moreover, within the group of young people living in Centre-Northern regions, reported statistics show a noteworthy difference (about 20 %) between migrants' and native-born households' incomes. If offspring's educational achievements depend on family economic resources *ceteris paribus* we would expect greater school dropouts in Southern Italy and within migrants. Interestingly, young individuals with a mixed origin [see column (5)] are more similar to migrants [column (4)] than to natives [column (3)], at least in terms of equivalent household income.

Together with parents' education level and households' incomes, a further determinant of families financial resources is given by the family wealth, here captured by owning the house in which the family live. About 70 % of the sample lives in a family-owned house. This percentage is slightly lower among those whose parents moved from Southern Italy, who are more likely to live in a rented house.

Moving to the outcome of the empirical analysis, the last row of the table reports the percentage of early school leavers in the different groups. The highest percentage of early school leavers is in the Southern Italy, where more than one youth in five drops education with at most the compulsory schooling leaving certificate. In the other Italian regions, this percentage is the half, but in Centre-Northern regions, migrants' offspring have a higher probability to drop early education than the corresponding native-born group. Again, the behaviour of youths with a mixed origin (parents born in different areas) is more similar to that of natives. These statistics seem to evidence an uncomplete process of assimilation of migrants' offspring in terms of educational achievements in Northern Italy. Indeed, although their outcomes are better than those of who remained in Southern Italy, there is still a gap with respect to the native born of the same age. In the following empirical analysis, we will assess to what extent these are genuine differences or the result of different households' observable characteristics and general economic conditions in the area of residence.

11.4 Results

The empirical setup is simple and based on reduced-form linear models for the probability to be an early school leaver, i.e. to drop out school just after compulsory schooling or during high school, without getting the corresponding diploma. The approach we take involves pooling data from all surveys and running regressions of the following form:

$$Early_i = \alpha + \delta * migr\_status_i + \beta x_i + \varepsilon_i$$

where $Early_i$ is an indicator that takes the value of one if the individual withdrew from education system at the end of compulsory schooling (generally at the age of 14), zero otherwise; x is a set of regressors which will be progressively enriched, as explained below. All specifications include a gender dummy, 16 cohort dummies for the year of birth, six time dummies for the survey's years and a set of dummies concerning the origin of individuals (*migr_status*), which are of our main interest. One concern is the potential endogeneity of the migration status, which imposes particular attention in the interpretation of results; in principle, second generation migrants might be a selected group to the extent that their parents migrated according to some characteristics that are transmitted within the family and correlated with education choices of offspring.[9] Although data do not provide retrospective information or recall questions at the time of parents' migration, the inclusion of the schooling level of both parents and the current financial status of the family, which are in general very correlated with their corresponding past levels (and with second generation migrants' education decisions) should be useful to (at least partly) control for selection problems.[10]

In addition to the role played by parental background, we will pay attention also to local labour market indicators—the youth unemployment rate (15–24 years old) by region and gender at the time in which individuals had the option of dropping out after compulsory education (i.e. when he or she was 14-year-old).[11] Several papers underlined the importance of these aspects for school-leaving

[9]For example, if parents of second generation migrants were low-income or low-educated individuals in their origin area, and this means something for the value given to education and for the amount of economic resources, they are willing to invest in the education of their offspring; OLS estimates are biased and inconsistent.

[10]Despite it is very difficult to evaluate empirically these issues, in Tables 11.3 and 11.4, we analyse the sensitivity of results to the inclusion/exclusion of family variables, which is helpful to better understand how the drop-out decision of second generation migrants are affected by background characteristics (i.e. the direction of the selection bias).

[11]In alternative to the (regional and gender-specific) youth unemployment rate, other measures of unemployment may capture different features of labour market conditions. For example, one could use the ratio between rates of youth and adult (over 25 years old) unemployment. Unfortunately, the time series of the latter were not available by region and gender until recently and cannot be used for our purposes. We experimented by estimating specifications that included alternative measures

patterns (Micklewright 1989; Micklewright et al. 1990). On the one hand, current unemployment of similar age individuals would discourage school leaving as it decreases the value of work. On the other hand, high unemployment rates are an overall indicator of the regional socio-economic conditions. In Italy, poorer and less-developed areas have in general high unemployment rates, which may discourage investments in education by reducing their expected returns (Micklewright et al. 1990). Then, the net effect of unemployment is a matter of empirical investigation. We also include a set of dummies for the year of birth of the children in order to capture any cohort effect and a set of time dummies for the survey's year to pick up the general evolution of socio-economic aggregates affecting education decisions as well as general trends in education behaviour.

Main findings are in Tables 11.3 and 11.4 and refer to the two different characterisation of migration discussed above. In Table 11.3, the youth's migration is defined in terms of the household head origin; in Table 11.4, we use the characterization based on the origin of both the household head and his/her spouse. The migration status is summarised by a set of (different across tables) dummies which separately identifies natives, second generation migrants and (only in Table 11.4) youths with mixed origin.[12] Both in Tables 11.3 and 11.4, the excluded category are youths born and living in Southern Italy. Each table presents estimates on the whole sample and by gender, in order to test whether youths' origin, together with observed households' and other characteristics, plays different roles in males' and females' educational outcomes. For each model, we estimate three specifications: the first [columns (1), (4) and (7)] includes only the origin's dummies (plus basic controls for gender, cohort and survey's year dummies). In the second [columns (2), (5) and (8)], we add family characteristics, while in the third [columns (3), (6) and (9)], we also include the gender-specific regional youth unemployment rate (15–24 years old) when the individual was at the age of 14.

Overall, basic results from the first specification confirm the descriptive evidence of Table 11.2: natives and second generation migrants born in the Centre-North are less likely to drop out education earlier than young individuals (born and) living in the South. Looking at Table 11.3, the differences are higher for natives (−14 %) than for second generation migrants (−10 %) and larger for males than for females.

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of unemployment: either the absolute overall regional unemployment rate or the relative youth unemployment rate (ratio between the youth unemployment rate and the overall unemployment rate) instead of the absolute youth unemployment rate. None of the two definitions turned out to play any statistically significant role in the estimates. One problem with the relative youth unemployment rate is that it varies much less than its absolute value, leading di per se to less precise estimates. Overall, it seems that in a segmented labour market as the Italian one, the educational choices of young individuals are more influenced by the conditions of the youth's labour market, than by its overall performance.

[12]The migration status may correlate with unobservable school-leaving determinants such as ability or motivation. In our sample, the migration decision has been taken not by the individuals but by their parents. This is likely to attenuate endogeneity problems to the extent to which they are due to the family characteristics included in the analysis.

Table 11.3 South to Centre-North Internal migration and the probability of early drop out from education system (linear probability models) - Youth born and living in Centre-North: migration status based on Household Head (HH) origin

	All			Males			Females		
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
HH born in Centre-North	−0.141***	−0.0577***	−0.0318*	−0.155***	−0.0588***	−0.0269	−0.125***	−0.0491***	−0.0152
	(0.00971)	(0.00983)	(0.0164)	(0.0146)	(0.0148)	(0.0228)	(0.0124)	(0.0128)	(0.0217)
HH born in the South	−0.102***	−0.0559***	−0.0314	−0.123***	−0.0529**	−0.0236	−0.0739***	−0.0442*	−0.0107
	(0.0166)	(0.0161)	(0.0194)	(0.0232)	(0.0223)	(0.0264)	(0.0233)	(0.0230)	(0.0269)
Female	−0.0718***	−0.0655***	−0.0771***						
	(0.00898)	(0.00838)	(0.00959)						
Number of children		0.0217***	0.0218***		0.0207***	0.0208***		0.0240***	0.0240***
		(0.00549)	(0.00548)		(0.00753)	(0.00753)		(0.00784)	(0.00784)
Father vocat./upper second		−0.109***	−0.109***		−0.130***	−0.132***		−0.0817***	−0.0820***
		(0.00882)	(0.00883)		(0.0131)	(0.0130)		(0.0118)	(0.0118)
Father univ. degree		−0.0864***	−0.0886***		−0.106***	−0.109***		−0.0504***	−0.0522***
		(0.0107)	(0.0108)		(0.0158)	(0.0159)		(0.0144)	(0.0145)
Mother vocat./upper second		−0.0848***	−0.0858***		−0.116***	−0.116***		−0.0550***	−0.0567***
		(0.00872)	(0.00878)		(0.0131)	(0.0132)		(0.0114)	(0.0114)
Mother univ. degree		−0.0879***	−0.0882***		−0.117***	−0.118***		−0.0565***	−0.0566***
		(0.0101)	(0.0102)		(0.0149)	(0.0150)		(0.0133)	(0.0132)
Log (family equiv. income)		−0.0485***	−0.0466***		−0.0477***	−0.0453***		−0.0528***	−0.0503***
		(0.00963)	(0.00971)		(0.0140)	(0.0140)		(0.0131)	(0.0132)

Family-owned house		−0.106***	−0.105***		−0.108***	−0.107***		−0.107***	−0.106***
		(0.0122)	(0.0121)		(0.0178)	(0.0177)		(0.0162)	(0.0160)
Youths reg. unem. rate at age 14			0.00108*			0.00158*			0.00122*
			(0.000558)			(0.000871)			(0.000722)
Constant	0.0228	0.524***	0.466***	−0.0909**	0.425***	0.343**	0.0370	0.544***	0.469***
	(0.0335)	(0.0930)	(0.0974)	(0.0413)	(0.132)	(0.139)	(0.0395)	(0.132)	(0.138)
Observations	11,458	11,458	11,458	6,122	6,122	6,122	5,336	5,336	5,336
R^2	0.063	0.165	0.166	0.067	0.178	0.179	0.052	0.149	0.150

Note see also below. HH born in Centre-North are the Centre-North natives. HH born in the South are the 2nd generation internal migrants from the South to the Centre-North, ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 11.4 South to Centre-North Internal migration and the probability of early drop-out from education system (linear probability models) - Youth born and living in Centre-North: migration status based on Household Head (HH) and his/her spouse (Sp) origin

	All			Males			Females		
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
HH and Sp born in Centre-North	−0.142***	−0.0569***	−0.0315*	−0.155***	−0.0558***	−0.0237	−0.127***	−0.0502***	−0.0166
	(0.00981)	(0.00996)	(0.0166)	(0.0149)	(0.0150)	(0.0231)	(0.0125)	(0.0130)	(0.0218)
HH and Sp born in the South	−0.0577**	−0.0205	0.00303	−0.0676*	−0.00753	0.0217	−0.0419	−0.0225	0.0103
	(0.0258)	(0.0244)	(0.0263)	(0.0352)	(0.0322)	(0.0345)	(0.0375)	(0.0373)	(0.0386)
HH and Sp born in differ. areas	−0.140***	−0.0844***	−0.0597***	−0.172***	−0.104***	−0.0732***	−0.0989***	−0.0524***	−0.0186
	(0.0140)	(0.0139)	(0.0183)	(0.0197)	(0.0199)	(0.0251)	(0.0199)	(0.0192)	(0.0260)
Female	−0.0715***	−0.0654***	−0.0767***						
	(0.00898)	(0.00838)	(0.00959)						
Number of children		0.0212***	0.0213***		0.0199***	0.0200***		0.0240***	0.0239***
		(0.00549)	(0.00549)		(0.00754)	(0.00753)		(0.00785)	(0.00786)
Father vocat./upper second		−0.109***	−0.110***		−0.132***	−0.133***		−0.0816***	−0.0819***
		(0.00885)	(0.00886)		(0.0132)	(0.0131)		(0.0118)	(0.0118)
Father univ. degree		−0.0871***	−0.0892***		−0.107***	−0.110***		−0.0504***	−0.0522***
		(0.0107)	(0.0108)		(0.0158)	(0.0159)		(0.0144)	(0.0144)
Mother vocat./upper second.		−0.0838***	−0.0849***		−0.115***	−0.115***		−0.0543***	−0.0560***
		(0.00872)	(0.00878)		(0.0132)	(0.0133)		(0.0113)	(0.0114)
Mother univ. degree		−0.0864***	−0.0867***		−0.114***	−0.116***		−0.0559***	−0.0560***
		(0.0101)	(0.0102)		(0.0149)	(0.0151)		(0.0132)	(0.0132)
Log (family equiv. income)		−0.0487***	−0.0468***		−0.0478***	−0.0455***		−0.0529***	−0.0504***
		(0.00963)	(0.00971)		(0.0140)	(0.0140)		(0.0131)	(0.0133)

Family-owned house		−0.106***	−0.105***		−0.109***	−0.107***		−0.107***	−0.105***
		(0.0122)	(0.0121)		(0.0178)	(0.0177)		(0.0162)	(0.0160)
Youths reg. unem. rate at age 14			0.00106*			0.00159*			0.00121*
			(0.000558)			(0.000871)			(0.000723)
Constant	0.0253	0.530***	0.473***	−0.0870**	0.433***	0.351**	0.0391	0.546***	0.471***
	(0.0334)	(0.0929)	(0.0973)	(0.0414)	(0.132)	(0.139)	(0.0391)	(0.132)	(0.138)
Observations	11,458	11,458	11,458	6,122	6,122	6,122	5,336	5,336	5,336
R^2	0.065	0.166	0.167	0.068	0.180	0.180	0.053	0.149	0.150

Note The binary dep. var. is 1 when the individual achieves at most the lower second degree. All the regressions include a set of 16 cohort dummies for the year of birth and six time dummies for the survey's years. Excluded categories: born in Southern Italy, mother lower secondary or less and father lower secondary or less. HH and Sp born in Centre-North are the Centre-North natives. HH and Sp born in the South are the 2nd generation internal migrants from South to Centre-North. HH and Sp born in differ. areas are the youths with 'mixed' origin. Robust standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

The finer disaggregation of Table 11.4 suggests that what really matters is having both parents from the South (−5.7 % probability to drop out than youths living in the South). Individuals with only one parent from the South (mixed origin) have the same probability of dropping out than youths with both the household head and his/her spouse from the Centre-North.

The findings shown in the specification that includes family characteristics underline that the parental background plays a relevant role in early school drop-out decisions. In particular, we find a positive effect of the educational level of both parents. This is a well-known result of the empirical literature, and it underlines the importance of cultural family background during attendance of education, as well as for the successfulness of the human capital accumulation process (e.g. Haveman and Wolfe 1995).

Similarly to previous findings (see, for instance, Micklewright 1989), we find a negative effect of family (equivalent) income, which is consistent with the standard human capital model where education is a normal good. The number of siblings increases the probability of dropping out, especially for females. Since we simultaneously account also for the dimension of the family on the available economic resources by using equivalent incomes, the coefficient of the number of siblings represent the effect of sharing other family resources, such as parental cares and time. On the contrary, youths of both genders living in a family-owned house are less likely to drop out school at an early stage. House ownership represents a proxy for the overall family wealth and the possibility to run into debit to finance offspring education, and it is positively associated with children's educational outcomes.

Tables 11.3 and 11.4 also show that the estimated effects of being a second generation migrant are affected by the presence of family characteristics among the regressors. Once we account for them, in Table 11.3, the effect of being born in the Centre-North, instead of in the South, on the probability to drop education after compulsory schooling is still negative but to a smaller extent (5.7 % instead of 14 %). More importantly, among youths born in the Centre-North, there are almost no differences between natives and second generation migrants [see Column (2)], and this is true for both males and females [columns (5) and (7), respectively].

When in Table 11.4 we use the stricter definition of migration based on the origin of both the household head and the spouse, second generation migrants have now the same probability to leave school after compulsory education than same age individuals from the South. Interestingly, the youths with a lower probability of an early school exit are those with a mixed origin (8.5 % less than similar individuals born in the South), especially among males.

The proposed sensitivity analysis then confirms that without controlling for current parental and family characteristics—which are potentially greatly correlated with the determinants of the decision to migrate—the negative effect of migration status, however defined, would be overestimated.

Concerning the role played by socio-economic conditions in the region of residence, we find that in Italy, youths' unemployment rates when the individual is 14 years old negatively affect the probability to study beyond compulsory schooling. This result contributes at explaining the lower educational achievement in Southern

Italy where unemployment is higher and, consequently, there are poorer socio-economic conditions, high uncertainty and lower expected returns to education.

Quite interestingly, this additional control explains a non-negligible share of the differential between Centre-Northern and Southern youths in terms of the probability to drop out school early. Particularly, in Table 11.3, the coefficient associated with both natives and second generation migrants is still negative (less likely to drop out) but smaller (from about 6 to 3 %) for both; in Table 11.4, the effect remains insignificant in the case of migrants, and it becomes (still negative but) smaller in the case of natives and mixed origin. Overall, these results suggest that in Italy, there are more incentives to invest in education where there is less uncertainty and the economy goes better (in the Centre-North), especially for natives.

Gender-specific estimates reveal that differences in the probability of studying after compulsory schooling between individuals born in Centre-North and South as well as between natives and second generation migrants born in Centre-North tend to vanish once we control for both family and socio-economic characteristics. The worst education performances showed in the descriptive statistics by Southern women are then explained by poorer parental background and by lower opportunities in the labour market. The effect of household and context conditions is important also for males: once controlled for that, the probability that males living in Centre-North drop out early school is lower than similar individuals living in Southern area only for individuals with a mixed origin: the effect is not statistically different from zero in the case of second generation migrants from the South.

The availability of data from a rather large time interval (12 years, from 1998 to 2010) allows analysing the evolution of the effect of internal migration on early school leaving, namely whether the coefficients of origin dummies remained stable in the period considered. To this purpose, we estimate a specification that includes the full set of regressors of columns (3) of Tables 11.3 and 11.4, plus interactions between the time dummies and the migration status variables. The coefficients of the interacted variables are reported in Table 11.5. Overall, the main result in terms of probability to withdraw from education is that the differences between youths living in the South of Italy, youths living in the North from parents born in the North and second generation migrants decrease over time. Adopting the wider definition of migration status (based on Household Head origin only), we find that over time, the three groups of individuals became more similar. Overall, Table 11.5 suggests that youths with the household head born in the Centre-North have a lower drop-out probability than the reference group (individuals living in the South with a Household Head born in the South) until mid-2000 decade. Similarly, the result that second generation migrants and individuals living in the South have comparable drop-out probability over the whole period hides the fact that until half of the past decade, the former had drop-out rates comparable to people with Northern parents. This evidence points in the direction of a reduction over time in the degree of both within and between heterogeneity in terms of early education achievements: higher integration between 'natives' with parents from the North and second generation migrants within the Centre-Northern regions; less differences between people born in the Centre-North and South of Italy.

Table 11.5 The evolution of the internal migration effect on early drop-out probability over time (linear probability models with interacted origin and time dummies)

Migration status based on household head origin		Migration status based on both household head and spouse origin	
Interactions of the time dummies with:		Interactions of the time dummies with:	
HH born in Centre-North		*HH and Sp born in Centre-North*	
1998	−0.0543	1998	−0.0498
	(0.0340)		(0.0347)
2000	−0.0799***	2000	−0.0764***
	(0.0256)		(0.0259)
2002	−0.0587**	2002	−0.0560**
	(0.0266)		(0.0269)
2004	−0.0576**	2004	−0.0543**
	(0.0250)		(0.0252)
2006	−0.0235	2006	−0.0286
	(0.0286)		(0.0287)
2008	0.0510	2008	0.0488
	(0.0264)		(0.0266)
2010	0.00362	2010	0.00616
	(0.0281)		(0.0285)
HH born in the South		*HH and Sp born in the South*	
1998	−0.106***	1998	−0.0179
	(0.0392)		(0.0649)
2000	−0.0721**	2000	−0.0563
	(0.0363)		(0.0528)
2002	−0.0187	2002	0.0488
	(0.0418)		(0.0567)
2004	−0.0904***	2004	−0.123***
	(0.0320)		(0.0372)
2006	−0.0154	2006	0.0143
	(0.0433)		(0.0672)
2008	0.01000	2008	0.0279
	(0.0347)		(0.0491)
2010	0.0566	2010	0.132
	(0.0621)		(0.0939)
		HH and Sp born in different areas	
		1998	−0.135***
			(0.0372)
		2000	−0.101***
			(0.0316)

(continued)

Table 11.5 (continued)

Migration status based on household head origin	Migration status based on both household head and spouse origin	
Interactions of the time dummies with:	Interactions of the time dummies with:	
	2002	−0.0968***
		(0.0346)
	2004	−0.0714**
		(0.0335)
	2006	−0.00232
		(0.0432)
	2008	0.0375
		(0.0423)
	2010	−0.0541
		(0.0356)

Note Estimates are obtained from the specification of Tables 11.3 and 11.4 with the full set of regressors, plus interactions between time and family origin dummies (and without the constant). We report only the coefficients of the interactions. In the first column, the migration status is based on Household Head (HH) origin; in the second column, it is based on Household Head (HH) and his/her spouse (Sp) origin. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

11.5 Concluding Remarks

This chapter investigates the determinants of the probability of completing education with (at most) compulsory schooling certificate in Italy among new generations. Among several factors providing information on parental background and family financial condition, we focus on the family origin. If the schooling system fails to provide migrants with an adequate level of human capital, the speed of their integration may be consistently reduced. This is true not only for immigrants from abroad, but it is also important for the integration of internal migrants, especially in countries such as Italy, which still experiences internal massive flows from less to more developed areas.

Regression results showed that parental education and family financial resources are among the main determinants of children's outcomes. Living in a region characterised by high youth unemployment rate at the time in which the decision to continue education beyond compulsory schooling is made discourages a further investment in education, and young people living in Southern Italy achieve on average lower educational levels. Thence, in line with Pastore (2012), the policy makers should focus interventions in the areas characterised by poor labour market opportunities in order to either reducing the early education drop-out rates as well as increasing the level of education available in these regions.

By controlling for family cultural and social resources, and by local labour market conditions, we find that young people with at least one parent from the Centre-North are less likely to drop out school but to a lesser extent than what descriptive statistics would suggest. Instead, the conditional probability of stopping education after compulsory schooling for the offspring born in Centre-North with both parents from the South is the same than that of youths born and living in the South. Hence, family characteristics and socio-economic conditions account for a non-negligible part of the observed differences in the probability of early drop out of youths with different origin and internal migration status.

According to these findings, the integration period of children with two non-native parents in the new area of residence does not necessarily allow to reach the same results of the natives in terms of educational achievements. This could happen for several reasons: migrants' families may have access to worse information about the local environment, the relative quality of schools, as well as they can rely on less-developed social networks giving assistance to both the family and the children. These results put into question the full integration of individuals of different regional origin living in Centre-Northern Italy in terms of educational achievements. The good news is that estimates that allow these effects to vary over the 12-year period covered by the data revealed that differences in the drop-out probability by origin status were significant especially until mid 2000s, to progressively decrease in more recent years. The ongoing homogenisation in terms of education decision at the end of compulsory schooling across Italian areas and across groups of youths defined by their origin cannot emerge from descriptive statistics which do not take into account the different backgrounds and financial conditions of individuals. If this is not a driven by cycle effect but confirmed as a structural trend in the next years, higher degrees of integration would be possible even in the close future.

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Appendix

Internal Migration in Italy: An Overview

Italian internal migration, mainly from Southern to Northern regions, is a well-recognised phenomenon and has received considerable attention by the demographic literature (Bonaguidi and Terra Abrami 1996; Bonifazi 1992; Bonifazi et al. 1999; Bonifazi and Heins 2000). The reason of this relevant internal mobility is the well-known Italian economic dualism owing to the presence of a highly developed and workforce demanding Northern area (only North Western up to the 1980s) and of a poorly developed and workforce supplying Southern area.

Although these internal migration flows never completely stopped during the last decades, they have been characterised by different patterns depending on the evolution of the relative economic conditions between different areas. Following Gabrielli et al. (2007), the Italian internal migration in the last 50 years can be then split into three main periods.

The first period, which goes from the mid-1950s up to the end of the 1960s, is characterised by massive internal migrations from Southern and North-Eastern regions to North-Western regions, the traditionally most industrialised area in Italy. The population redistribution reached its peak in Italy during the period 1960–1964. In particular, three North-Western regions (Piedmont, Lombardy and Liguria), hosting in their territory the so-called 'industrial triangle', increased their population by more than 10 per 1,000 inhabitants and, conversely, four Southern regions (Basilicata, Calabria, Puglia and Sardinia) lost the same inhabitants' percentage.

The second migration phase goes from 1970 to the mid-1990s and is characterised by a remarkable decrease in mobility across regions, especially in the first decade when the migration from Southern to Northern regions was nearly absent. Nevertheless, from the second part of the 1980s, the migration process restarted with some intensity even if it never reached the levels of the economic boom decades.

This pattern of limited but persistent migration from Southern regions continued during the last decade up to the mid-2000s with a shift of Southern migrants towards North-Eastern regions characterised, especially during the 1990s, by a remarkable economic acceleration. In particular, the year 2000 recorded the greatest flow in the last decades and around 150,000 individuals moved their residence from Southern to Centre-Northern Italy. According to recent data (Mocetti and Porello 2010), in the very last years, migration has returned to the levels of the mid-1990s even if the composition of the movers in terms of skills and educational level has radically changed.

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Chapter 12
The Effect of University Costs and Institutional Incentives on Enrolments: Empirical Evidence for Italian Regions

Claudia Pigini and Stefano Staffolani

Abstract We study the relationship between the enrollment decisions of Italian secondary school graduates and the cost of participating in higher education. In particular, we look into the role of incentives, such as scholarship grants, and of the supply of under-priced accommodation which are policy tools in the hands of regional institutes (Enti Regionali per il diritto allo Studio Universitario, ERSU). We provide empirical evidence by estimating a conditional logit model using the survey of 2004 secondary school graduates issued by the Italian Institute of Statistics (ISTAT). We find that enrollment costs are determinant in students university choices: on average, the elasticity of the probability of enrollment to tuition fees is −0.062, the one to expected grants is 0.028, and the one to expected rent is −0.022. Differences between regions are considerable: southern regions show lower elasticities, while small central and northern regions exhibit the largest ones.

Keywords Conditional logit model • Enrolment cost • Graduates' mobility • Regional differentials • University enrolment

JEL classification: C25, I21, I23, J24

12.1 Introduction and Motivation

The structure of the Italian Higher Education (HE henceforth) system has faced several changes during the last 15 years, mainly due to the need of increasing the graduation rate, one of the lowest among OECD countries: only 20.2 % of Italians between 25 and 34 years of age are graduates compared to the 37.1 % of the OECD

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average (OECD 2011). The "Bologna process"[1] deeply transformed the Italian HE system with the aim of reducing the drop-out rate and creating more educational opportunities. However, the introduction of the so-called "3+2" reform only had the desired effect in the short run, and it affected positively the enrollment rate but not the completion rate (Bratti et al. 2008). Nevertheless, individual inequalities remain in the accessibility to the Italian university system due to the low intergenerational mobility (see Checchi et al. 2013).

Italian students' low geographical mobility is another central issue in the debate on the Italian HE accessibility and completion. High geographical mobility should imply a certain degree of flexibility in the choice by secondary school graduates of which university to attend: in particular, it would ensure a "good" matching between the student's ability and preferences and the university. Moving to study implies higher costs of participation in HE that, in Italy, are usually sustained by the students' families. Even though the Italian university system is for the most part financed by the government, many of the other participation costs must still be sustained by the students' families as well: recently Ichino and Terlizzese (2013) raised crucial issues about the financing of the Italian HE system, such as how much tuition fees affect the enrollment rate and whether financial aid can facilitate the enrollment of poorer students. As a consequence, intergenerational mobility decreases and students from poor families will enroll in universities located close to home (Ordine and Lupi 2009). This may result in a "bad" student-university matching, which may, therefore, raise the drop-out probability.

In this work, we study the relationship between the enrollment decisions of Italian secondary school graduates and the cost of participating in HE: we add to the research on the Italian case by providing extensive empirical evidence on the sensitivity of enrollment rates to the costs perspective students should sustain to participate in HE, namely mobility costs and tuition fees. In addition, we investigate the role of incentives, such as scholarship grants and moving facilitation (underpriced accommodation), that may counteract the deterrence effect of HE monetary costs. Since, in Italy, incentives are managed by regional institutes ERSU,[2] our analyses are developed from a regional perspective.

By doing so, we also give some insight on the role of territorial variables, such as the unemployment rate (see also Pastore 2005) and the quality of life, on HE choices. As emphasized in some recent contributions (Aina and Pastore 2012; Caroleo and Pastore 2012), local labor market conditions can influence the enrollment decisions not only through the unemployment rate but also through overeducation. Differences in unemployment rates, overeducation, and skill premia between labor markets can push secondary school leavers to move outside of their region of origin in order to increase their opportunities for future jobs.

[1] A series of conferences in Paris (1998), Bologna (1999), Prague (2001), Berlin (2003), and Bergen (2005) whose goal was to achieve a higher degree of comparability between European HE systems.

[2] Regional agency for the right to education (Enti Regionali per il diritto allo Studio Universitario).

For the purpose of our analysis, we estimate a conditional logit model for enrollment and university choices of Italian secondary school graduates.[3] We use the Italian Institute of Statistics (ISTAT) survey of secondary school graduates in 2004 interviewed in 2007 linked with data on institutions' characteristics from the Italian Ministry of Education, University and Research (MIUR). We add the information on the socioeconomic condition of Italian provinces in 2003 using the indicators published by the magazine *Il Sole 24 Ore* and the 2003 popular university ranking of *Censis-Repubblica*.[4]

We find that enrollment costs play a major role in students university choices: on average, the elasticity of the probability of enrollment to tuition fees is −0.062, the one to expected grants is 0.028, and the one with respect to expected rent is −0.022. Our results are in line with those found for public universities in the USA by Hemelt and Marcotte (2008) using the Post-secondary Education Data System: from 1991 to 2007, on average, an increase of 100$ in tuition fees decreased enrollments of about 0.25 %, which is similar to our result for an increase of 100 euros (10 % on average in tuition fees).[5]

The remainder of the chapter is organized as follows: Sect. 12.2 contains a brief review of contributions that analyze students' HE choices as function of university characteristics; Sect. 12.3 briefly describes the estimation strategy and how post-estimation elasticities are computed; Sect. 12.4 presents regional descriptive statistics on enrollments and describes the variables used in our empirical analysis; Sect. 12.5 contains the estimation results and Sect. 12.6 concludes.

12.2 Literature Review

Theoretical and empirical effort has been put into understanding the behavior of secondary school graduates when facing the decision of whether to participate in HE and, if so, where to enroll. In particular, recent contributions have investigated

[3]The application of this estimation strategy to model HE choices was first proposed by Manski and Wise (1983) and followed in recent analyses by Long (2004) and Gibbons and Vignoles (2012). Drewes and Michael (2006) and Verboven and Kelchtermans (2010) use some variations of the conditional logit model: the rank-ordered conditional logit and the nested logit model, respectively.

[4]Staffolani and Pigini (2012) propose a theoretical model that describes the enrollment and university choices of secondary school graduates and an empirical analysis aimed to test its prediction. The work focuses on a general framework for students' choices that is based on HE costs as well as university quality, while it takes no account of the role of regional incentives. The reader will, however, be referred to Staffolani and Pigini (2012) for a more extensive description of the data.

[5]Earlier results can be found in Jackson and Weathersby (1975), Leslie and Brinkman (1987), Kane (1995), and Kane (1995). A compact review of these references can be found in http://www.hanoverresearch.com/2012/06/tuition-elasticity-student-responsiveness-to-tuition-increases/.

the determinants of HE choices in Italy with considerable attention to geographical accessibility of the HE system and to possible financial constraints to the choice of which university to attend. Agasisti and Dal Bianco (2007) first explored the determinants of students mobility finding distance to be one of its major deterrents. Their gravity model also suggests that, when a student moves she enrolls in a university located in an area with good socioeconomic conditions rather than choosing on the basis of that university's characteristics. The findings in Ordine and Lupi (2009) show that mobility is constrained by family income. Italian students tend to remain in their own region despite the Italian university system supplies different standards, which may allow a more efficient ability sorting across institutions. The theoretical model of Cesi and Paolini (2011) confirms both the previous results: geographical distance is a strong deterrent to university participation and choice. In addition, secondary school graduates will choose the closest university regardless of the quality of the university-student matching, based on institution's quality and student's ability.

While the findings of the above-cited contributions clearly suggest a negative effect of commuting and moving costs on university choices, the role of the tuition fees charged by universities in affecting HE choices has not been explored. These issues have been more extensively analyzed in other case studies. Long (2004) first examines both the decision of enrolling and into which college for the US from 1972 to 1992. Tuition and distance to the institutions negatively affect the decision of which college to attend; in turn, the negative effect of price and distance on the likelihood of enrolling attenuates over the years. In the particular case of intrastate migration in Georgia, Alm and Winters (2009) confirm the key role of distance in the choice of where to study. In the case of Canada, Frenette (2004, 2006) finds that a greater distance increases the likelihood of attending local colleges and students who live too far to even commute tend not to participate. Drewes and Michael (2006) suggest that the negative effect of price on the university choice attenuates when considering universities charging high tuition fees as they may be associated by students with the supply of better services. The contributions of Sá et al. (2004) and Verboven and Kelchtermans (2010) examine the cases of Netherlands and Flanders, respectively. The former stresses the role of geographical proximity in the enrollment probability along with the students ability and school background (a similar result is also presented in Spiess and Wrohlich (2010) for Germany and in Denzler and Wolter (2011) for Switzerland). Verboven and Kelchtermans (2010) analyze not only if and where to study but also which subject to study: they find that travel costs are a major determinant of the choice of where and what to study; geographical distance, however, seems not to affect the decision of going to university. This same result is found in Gibbons and Vignoles (2012): in UK, geographical distance has a negative role in the choice of the institution, which gets stronger for students coming from lower socioeconomic groups. However, there is only a weak link between geographical inaccessibility of the HE system and the decision to continue with tertiary education.

12.3 Estimation Strategy

We assume that each individual compares the expected utilities she can obtain from graduating in alternative universities and the utility achievable by not participating in HE: if the latter is greater than all the other utilities, the student will not enroll, otherwise she will enroll into the university that gives the highest utility. The econometric model used to describe such decision-making process is the conditional logit model (McFadden 1974), which was first advocated by Manski and Wise (1983) to model college choice. This approach has also been followed by Long (2004) and Gibbons and Vignoles (2012). The conditional logit model allows us to model the probability of choosing to enroll and, if so, in which university as a function of university characteristics. However, its fixed-effect nature does not allow for the inclusion of alternative-invariant covariates, such as individual characteristics. They should be interacted with alternative-varying characteristics or alternative-specific intercepts. However, such strategy would lead to an output of difficult interpretation. Another strategy is to estimate a multinomial logit model that would, however, exclude the possibility of including alternative-varying regressors among the covariates.[6]

We assume that student i chooses between $J + 1$ alternatives, of which J are Italian universities and one is the nonparticipation option. Whether to include this last alternative is a critical issue in applications of conditional logit models to HE choices. Long (2004) argues that the estimation of separate models avoids distortions in parameter estimates also because it is not clear whether the observed choice of non-enrollment is given by the student's actual decision or to the rejection of his or her applications. However, this misleading situation is not likely to occur when analyzing the case of Italy where neither applications are needed nor entry tests have to be passed to access the HE system.[7] An alternative approach would be to use a nested logit model as suggested in Verboven and Kelchtermans (2010). Therefore, we should define a nesting structure separating sets of comparable alternatives, and a natural choice would be to divide groups of faculties by macro-subjects. However, as we are not interested in the determinants of choosing a specific field of study but only in the relationship between university choice and its cost, we believe that an extremely time-consuming procedure, such as the estimation of a nested logit model, would be unnecessary in this case.

We, therefore, jointly analyze the university choice and the nonparticipation choice, including the latter in the set of the possible alternatives of the conditional logit model. It is quite straightforward to assign values of university characteristics

[6]More flexible tools that accommodate random utility models, such as multinomial probit or mixed logit models, are, in principle, the best choice in these cases. However, given the high number of student–university combinations in our dataset, the adoption of such models is computationally unfeasible.

[7]The faculties of Medicine and Architecture pose as an exception. However, applicants who cannot access these faculties have no obstacles in enrolling into other faculties without being selected.

in the non-enrollment alternative without making arbitrary choices.[8] The probability that student i chooses k among $J + 1$ alternatives is

$$\Pr(i \text{ chooses } k) = \Pr\left(V_{ik} > V_{ij}\right) \qquad \forall \quad j \neq k, j = 1, \ldots, J + 1 \tag{12.1}$$

where $J + 1$ are J Italian universities plus the nonparticipation alternative. In general, V_{ij} is the utility of alternative j for student i that is given by:

$$V_{ij} = x_{ij}'\beta + q_j'\gamma + z_h'\theta + \upsilon_{ij} \qquad \text{for} \quad i = 1, \ldots, n \quad \text{and} \quad j = 1, \ldots, J + 1. \tag{12.2}$$

In this setup, x_{ij} includes the regressors varying across alternatives and individuals, such as the distance between the location of student i and the location of university j. Instead, the set q_j contains institution characteristics as, for example, tuition fees. Finally, z_h includes variables that serve as proxy of the socioeconomic conditions of the province where the university is located (unemployment rate, quality of life, etc.), where the subscript h denotes the province, with $h = 1, \ldots, H$. As anticipated in Sect. 12.4, there are universities located in the same province so that $H < J$. Assuming that the υ_{ij} are independent and identically distributed as extreme value distribution, the probability P_{ik} of i choosing k is

$$\mathrm{P}_{ik} = \frac{e^{V_{ik}}}{\sum_{j=1}^{J+1} e^{V_{ij}}}. \tag{12.3}$$

Central to our paper is the effect evaluation of changes in key policy variables on the enrollment probability; in particular, we want to quantify the variation in regional enrollments in response to changes in tuition fees and incentives that are typically put forward by regional institutions (ERSU). To this aim, it is useful to compute direct elasticities to gain insight on the impact of changes in variables q_j on P_{ij}. In the conditional logit model, the direct marginal effect of a change in q on the probability of choosing alternative j can be computed as:

$$\psi_{ij,q_j} = \frac{\partial \hat{P}_{ij}}{\partial q_j} = \hat{P}_{ij}\left(1 - \hat{P}_{ij}\right)\phi\left(q_j, \gamma\right) \tag{12.4}$$

where $\phi\left(q_j, \gamma\right) = \frac{\partial V_{ij}}{\partial q_j}$. When the model specification is linear in q_j, $\phi\left(q_j, \gamma\right) = \gamma$. We define r to be the regional index, $r = 1, \ldots, 20$, and we compute regional elasticities as follows:

$$E_{\hat{P}_r, Q_r} = \bar{\psi}_{r,q_r} \frac{Q_r}{\hat{P}_r} \tag{12.5}$$

[8]Such assignment will be explained in detail in Sect. 12.4.

where $\bar{\psi}_{r,q_r}$ is the regional average marginal effect and

$$Q_r = \bar{q}_r * N_r$$
$$\widehat{P_r} = \sum_{j \in r} \widehat{P_j}$$

Q_r is the total amount of q in region r; $\bar{q}_r$ is the average q_j in region r; $\widehat{P_r}$ is the total probability of enrolling in region r; and $\widehat{P_j}$ is the average probability on enrolling in university j with $\widehat{P_j} = \frac{1}{n}\sum_{i=1}^{n} \hat{P}_{ij}$. N_r is the total number of enrolled students in region r in 2004.

12.4 Dataset Description

We combine datasets from various sources (see Table 12.1) in order to include variables on the individual and university level and some socioeconomic characteristics of the provinces where universities are located. At the individual level, we use the survey on studying and working experiences of secondary school graduates (Indagine sui percorsi di studio e lavoro dei diplomati) issued by the ISTAT. The students are interviewed 3 years after obtaining their secondary school *diploma*. We use the 2007 survey where 25,880 students, who obtained the title in 2004, were interviewed. The dataset contains information on the students' personal and household characteristics and on their educational background. We observe, in particular, the enrollment decision and, for the enrolled individuals, which university the student has enrolled into. In our analysis, we chose not to consider: universities attended by less that 20 individuals in the sample (so that we drop 142 observations); 371 students for whom we do not observe which university they have chosen (207 have enrolled abroad); 32 students enrolled in universities for foreigners; and 17

Table 12.1 Source of variables used in the conditional logit model

ISTAT	MIUR	CENSIS	SOLE 24 ORE
DISTANCE			
	FEES	*RANKING*	*EXP. RENT*
	PRIVATE		*POPULATION*
	EXP. GRANTS		*QUALITY OF LIFE*
	DELAYED GRADUATION		
	APTITUDE		
UNEMPLOYMENT[a]			

[a]ISTAT Labor Force Survey (Indagine sulle forze di lavoro)

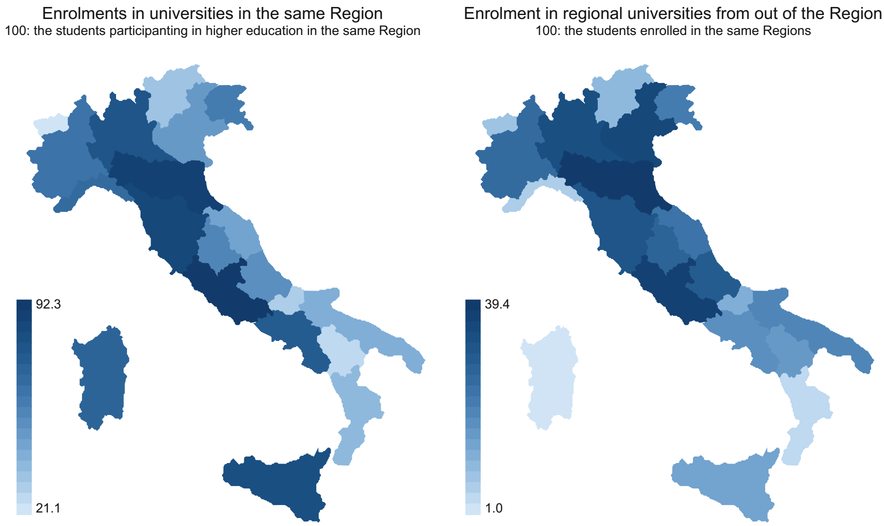

Fig. 12.1 Percentages of enrolled students staying or moving to Italian regions. *Source*: ISTAT, survey on studying and working experiences of Italian secondary school leavers (graduated in 2004, interviewed in 2007)

students enrolled in online universities.[9] Finally, we end up with a sample of 25,318 secondary school leavers and 79 universities.

One key information contained in these data is the student's province of residence during the secondary school attendance. We can therefore investigate regional mobility of Italian students by considering the attractiveness of Italian regions in two dimensions: by computing the percentage of secondary school graduates in a certain region who enroll in universities located in that same region and the percentage of enrolled students in a certain region coming from other Italian regions. These two statistics are represented in Fig. 12.1.[10] It clearly emerges that the ability to attract students is strongly differentiated between Italian regions: Emilia-Romagna and Lazio seem to be the most attractive as about 40 % of the students enrolled in those regions come from other parts of Italy, whereas these numbers for southern regions and islands are much lower (1 % for Sardegna).[11] Students' mobility can also be

[9]In the appendix, Fig. 12.3, based on UNESCU data, shows the number of foreign students enrolled in Italy and the number of Italian students enrolled abroad for the period 1999–2010.

[10]Detailed percentages are displayed in Table 12.5 in the appendix, where the first and third columns are plotted in the left and right panels of Fig. 12.1, respectively.

[11]Table 12.6 in the appendix, based on MIUR data, shows the evolution over time for the period 2001–2007 of the "attractiveness" of regional universities, computed by the ratio between the share of students enrolled in regional universities coming from outside the region on students enrolled in the region and the share of students enrolled in universities outside the region on enrolled secondary school leavers living in the region.

represented by flows between regions. For each region, Table 12.7 in the appendix shows which Italian regions have the highest enrollment rates, by the students' region of provenance. The largest flows of students among regions concern students from Valle d'Aosta moving to Piemonte, students from Trentino-Alto-Adige moving to Veneto, and students from Molise moving to Lazio. The dataset allows us to compute the distance between the student's province of residence and the province of each Italian university (measured in 100 km) that will be used in the empirical analyses (*DISTANCE*). This variable takes value zero for universities located in the same province of the student's residence during secondary school studies and for the non-enrollment option.

In order to estimate the conditional logit model, we need to reorganize the data such that the observational unit is the student-university combination. We, therefore, end up with a dataset of 2,025,440 observations given by the product between the 25,318 high school leavers and the 80 possible choices (79 universities plus non-enrollment).

Information on tuition fees, scholarships granted by universities, and the number of assigned accommodation in 2003 is available on the website MIUR. In the estimation, we use the *EXPECTED GRANTS* that are computed by multiplying the amount of grants by the ratio of students who obtained the scholarship over the number of students enrolled in each university in 2003. We also use the *EXPECTED RENT* that is based on the data of monthly renting of a 20 square meters place in the province (data from *Il Sole 24 Ore*), multiplied by the unity minus the probability of getting an accommodation in a student residence. Fees, grants, and rent are set to zero for the non-enrollment option. Additionally, rent is set to zero for those alternatives that have universities located in the same province as the student residence.

Therefore, we have three variables concerning the cost of attending each of the 79 Italian universities considered in the sample. Table 12.2 contains some descriptive statistics of these variables for the Italian macro-areas. In general, the costs of attending a university are higher in the northern regions, where, however, more grants are available to the students. Cost variables are set to zero for the non-enrollment choice.

In order to add some control variables to our specification, we link the ISTAT dataset with other information on universities coming from other sources. We use the popular Italian university ranking (*RANKING*) of *Censis-Repubblica* of 2003[12]: we include this variable in our empirical analyses to control for the university quality in students' choices. Even though ranking is only an imperfect measure of the university quality, it still poses an available signal to the student of universities' reputation. For secondary school leavers who decided not to enroll, we assign the

[12]The methodology note that describes the computation of the university ranking can be found in http://www.repubblica.it/speciale/2002/censis/indicatori.html.

Table 12.2 Descriptive statistics for *FEES*, *EXP. GRANTS*, and *EXP. RENT* in the Italian macro-areas

Macro-area	Stat.	*FEES*	*EXP. GRANTS*	*EXP. RENT*
North-West	Mean	12.21	17.15	1.51
	Min	3.95	5.28	0.00
	Max	58.56	24.49	4.33
	Sd	10.32	2.76	1.71
North-East	Mean	8.93	18.43	1.56
	Min	5.97	12.78	0.00
	Max	28.85	25.62	5.94
	Sd	2.58	4.38	1.51
Center	Mean	8.19	14.50	1.59
	Min	3.93	7.09	0.00
	Max	46.44	25.36	3.83
	Sd	6.32	5.18	1.52
South	Mean	5.04	8.02	0.68
	Min	3.15	2.92	0.00
	Max	9.42	14.30	2.47
	Sd	1.25	2.83	0.87
Island	Mean	3.91	8.96	0.59
	Min	3.21	5.00	0.00
	Max	9.33	16.00	2.90
	Sd	0.76	3.53	0.81
Total	Mean	8.33	14.43	1.29
	Min	3.15	2.92	0.00
	Max	58.56	25.62	5.94
	Sd	6.49	5.68	1.47

Fees and grants are expresses in 100 euros per year. Rent is expressed in 100 euros per month. It is set to 0 for those alternatives that have universities located in the same province as the student residence and for the non-enrollment option
Source: ISTAT, survey on studying and working experiences of secondary school leavers

ranking value of 6.4: this choice is motivated by thinking of university quality as some measure of returns to education. Since in 2003 the average wage premium of a university degree over a secondary school title was about 30 % (OECD 2003), we set a ranking value that stands in the same proportion. The model specification also includes ranking square and cube to account for the possibility that the optimal level of university standard may not necessarily correspond to the maximum ranking available.

Control variables related to the socioeconomic characteristics of the provinces where the universities are located are also included.[13] In particular, we use the

[13]Their relevance is discussed in Agasisti and Dal Bianco (2007).

indicator of *QUALITY OF LIFE*, yearly provided by *Il Sole 24 Ore*, as an indicator of the environmental attractiveness. From the ISTAT Labor Force Survey (indagine sulle forze di lavoro) of 2003, we use the unemployment rate (*UNEMPLOYMENT*) and the *POPULATION*[14] of the university province. Moreover, we investigate the effect of indirect costs that may potentially be sustained by the student if, in certain universities, it is likely to take longer to graduate. Therefore, from MIUR data, we include the variable *DELAYED GRADUATION* that represents the share of students, in each of the universities considered, who take more than the legal length of studies to graduate. This variable represents a proxy of the effective length of studies. Descriptive statistics on ranking and other control variables are displayed by Italian macro-areas in Table 12.8 in the appendix.[15]

From MIUR data, we also extract a control variable which takes value 1 if the university is private and 0 if public (*PRIVATE*). The majority of Italian universities are public (66 of the 79 considered in our study) and their fees are relatively low compared to those charged by private universities.[16] We also include the *APTITUDE* variable: for each individual, it is built considering the correspondence between the field of secondary studies and the disciplinary fields offered by each university. If *APTITUDE* is equal to one, there is a good correspondence between previous studies and offered fields.

12.5 Estimation Results

The estimation results of the conditional logit model are presented in Table 12.3, where estimates of four different model specifications are included. The first column (model (1)) shows the results of the model estimation using the baseline specification that includes fees, expected grants, expected rent, the geographical distance, and the other control variables listed in Sect. 12.4.

Models (2) and (3) further investigate the effect of tuition fees in students' choices in terms of differences in enrollment costs between public and private universities. We first drop the dummy *PRIVATE* in model (2) and consider the interaction between *PRIVATE* and *FEES* in model (3). In model (4), we add the variable *DELAYED GRADUATION* that represents the share of students, in each of the universities considered, who take more than the legal length of studies to

[14]We want to control for dimension as the return to skill may be higher in big cities. See Addario and Patacchini (2007).

[15]More detailed descriptive statistics on all the variables included in the conditional logit specification, disaggregated by universities and Italian provinces, are available in Staffolani and Pigini (2012).

[16]Average tuition fees are 720 euros in public universities and 2,480 euros in private ones.

Table 12.3 Estimation results: conditional logit model

	(1)		(2)		(3)		(4)	
Variables	Coeff.	St. err.	Coeff.	St. err.	Coeff.	St. err.	Coeff.	St. err.
Dependent var.: *CHOICE*								
Independent vars								
FEES	−0.032	(0.003)	−0.068	(0.002)	−0.056	(0.005)	−0.031	(0.003)
EXP. GRANTS	0.008	(0.002)	0.012	(0.002)	0.012	(0.002)	0.007	(0.002)
EXP. RENT	−0.098	(0.010)	−0.070	(0.010)	−0.083	(0.010)	−0.080	(0.010)
DISTANCE	−2.692	(0.024)	−2.694	(0.024)	−2.706	(0.024)	−2.702	(0.024)
DISTANCE SQ.	0.352	(0.005)	0.352	(0.005)	0.355	(0.005)	0.354	(0.005)
DISTANCE CUBE	−0.015	(0.000)	−0.015	(0.000)	−0.015	(0.000)	−0.015	(0.000)
RANKING	−117.78	(3.03)	−117.98	(3.01)	−118.14	(3.04)	−114.13	(3.06)
RANKING SQ.	13.788	(0.362)	13.807	(0.359)	13.850	(0.362)	13.382	(0.364)
RANKING CUBE	−0.533	(0.014)	−0.533	(0.014)	−0.536	(0.014)	−0.518	(0.014)
QUALITY OF LIFE	0.401	(0.042)	0.368	(0.043)	0.310	(0.042)	0.407	(0.042)
UNEMPL. RATE	−6.158	(0.482)	−6.417	(0.476)	−6.231	(0.476)	−5.926	(0.485)
POPULATION	0.421	(0.012)	0.418	(0.012)	0.412	(0.012)	0.411	(0.012)
APTITUDE	1.106	(0.032)	1.132	(0.033)	1.141	(0.033)	1.134	(0.033)
PRIVATE	−1.038	(0.053)			−1.343	(0.087)	−1.099	(0.055)
FEES × PRIVATE					0.028	(0.005)		
DELAYED GRAD.							−0.552	(0.093)
Log-lik.	−46974.89		−46957.71		−47225.99		−46961.56	
Pseudo-R^2	0.5776		0.5767		0.5743		0.5767	
LR test :	$\chi^2_{(14)} = 68499.94$		$\chi^2_{(15)} = 68169.50$		$\chi^2_{(13)} = 66777.12$		$\chi^2_{(15)} = 68469.92$	
Observations	2,025,440							

All coefficients are statistically significant with p-value < 0.01. Standard Errors are adjusted for 25,318 clusters (students) graduate. This variable represents a proxy of the effective length of studies which should account for indirect costs that may potentially be sustained by the student if, in certain universities, it is likely to take longer to graduate. All the results presented in Table 12.3 show a positive effect of expected grants and a negative effect of tuition fees and expected rents on university choice. Higher enrollment costs, nets of the contribution of regional institutes through under-priced accommodation, and scholarship grants reduce the probability of enrollment.[17] It is worthwhile to note that in specification (2), where *PRIVATE* is not included, the coefficient associated to *FEES* is more than double the ones in specification. As expected, tuition fees have a stronger effect on the choice of enrolling in a private university (model 4). The negative coefficient of *DELAYED GRADUATION* in model (3) shows that the indirect cost of facing a possibly longer length of studies negatively affects university choices.

The cubic relationship between distance and choice of university can reasonably describe the behavior of Italian secondary school leavers: it may be conjectured that a student is more likely to enroll in a university close to home; therefore, the probability of enrolling in a university located in other provinces decreases in the cost and time of commuting; however, for those universities located too far to commute, the decreasing effect on the choice probability attenuates. This is probably due to moving and renting costs being somewhat constant: it makes sense that transportation and renting costs may not be extremely different for various distances once the student has decided to move in order to enroll. The left panel of Fig. 12.2 confirms this line of reasoning: the probability of enrolling is decreasing for distance below 500 km and remains nearly constant for distance between 500 and 1,200 km.

Nonlinearity also reflects the individual heterogeneity in the choice of university. The optimal level of university standard that does not necessarily corresponds to the maximum ranking available: students may self-sort according to their individual ability across different university standards on which the level of effort required to finish the studies may depend on. This result is also predicted by the theoretical model in Staffolani and Pigini (2012). The right panel of Fig. 12.2 shows that, on average, students prefer the lowest ranked university or medium/high-ranked ones.[18]

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[17]The coefficient presented in Table 12.3 are strongly influenced by the familiar background of students. For instance, by selecting the sample of students coming from the richest families (the ones where the highest job position is chief executive officers, executive or self-employed), we obtain the following coefficients: tuition fees −0.007, rent −0.089, grants are not statistically significant. By selecting students coming from poorer families (the one where the breadwinner is executive white collar, blue collar, or unemployed), the three coefficients are strongly higher (in absolute value): −0.07 for fees, 0.007 for grants, and −0.114 for rent. Therefore, regional policies aimed to provide incentives in terms of cost reduction have a strong redistributing effect of enrollment opportunities and university choices for different subgroups of the population (see Staffolani and Pigini 2012).

[18]Quartic specifications in distance and university ranking have also been tested. Results, however, are not remarkably different.

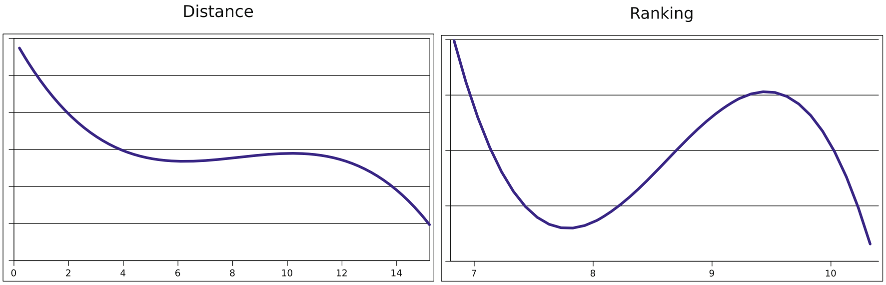

Fig. 12.2 The relationship between the estimated probability of enrolling, distance, and ranking

In line with the results of Agasisti and Dal Bianco (2007), Table 12.3 shows that the socioeconomic condition of the university province plays a key role in the choice of which institution to attend: the expected signs of the quality of urban life and unemployment rate suggest that the search of better environments and opportunities may hide behind the university choice. As well, the dummy variables for private universities and *APTITUDE* all have the expected sign.

As introduced in Sect. 12.3, we compute elasticities to gain some insight into the effects of variations in key policy variables for academic and regional institutions on university choice and enrollment decision. Table 12.4 displays direct elasticities of the probability of enrollment to university tuition fees, expected grant, and expected rent, computed by evaluating Eq. (12.5) in the estimated parameters of model (1). Instead of reporting these elasticities for the university in the sample, the table shows average elasticities for each Italian region. These elasticities are computed by weighting regional universities with the number of enrolled students.

The elasticity of the enrollment probability faced by universities to changes in their own fees is, on average, −0.062 so that an increase in fees of 10 % decreases the enrollment rate in the universities located in the "average" region of 0.62 percentage point.[19] The elasticities are strongly differentiated across regions, from a minimum of −0.018 in Puglia and −0.019 in Campania to a maximum of −0.172 in Umbria and −0.165 in Liguria. These last two regions are small and located in areas with a high number of universities in neighbor regions. In general, southern Regions seem to show lower elasticities. On average, the elasticity of the enrollment probability to expected grants is 0.028, the one to expected rent is −0.022. Across Italian regions, differences are remarkable: as above, enrollment in universities located in Umbria and Liguria seems to be affected more by the enrollment costs,

[19]We also computed the average elasticity between universities, obtaining the result of −0.3, that is the same presented in Staffolani and Pigini (2012). It is higher, in absolute value, than the average elasticity computed between regions. These results are nevertheless coherent: in fact, considering regions, we do not take into account the substitution between enrolling in universities located in the same region.

Table 12.4 Direct elasticities of the probability of enrolment to university fees, expected grants, and expected rent, by region

	FEES	*EXPECTED GRANTS*	*EXPECTED RENT*
Piemonte	*−0.042*	*0.020*	*−0.015*
Valle d'Aosta	−0.115	*0.037*	−0.012
Lombardia	−0.039	0.009	*−0.015*
Trentino-Alto Adige	*−0.071*	0.047	*−0.017*
Veneto	*−0.059*	*0.021*	−0.048
Friuli-Venezia Giulia	*−0.078*	0.041	−0.035
Liguria	−0.165	0.072	−0.042
Emilia Romagna	−0.033	0.015	−0.014
Toscana	*−0.063*	*0.033*	−0.041
Umbria	−0.172	0.094	−0.064
Marche	−0.029	0.016	−0.014
Lazio	−0.033	0.008	*−0.020*
Abruzzo	−0.037	0.011	*−0.020*
Molise	−0.084	*0.030*	−0.012
Campania	−0.019	0.006	−0.008
Puglia	−0.018	0.007	−0.010
Basilicata	−0.096	0.043	*−0.020*
Calabria	−0.028	*0.018*	−0.010
Sicilia	−0.029	0.011	−0.014
Sardegna	−0.028	*0.023*	−0.012
National Mean	−0.062	0.028	−0.022

The *Italic* fonts indicates that elasticities are not significantly different from the national values at 5 %

whereas enrollment in universities located in the south seems to be less sensitive to their increase.

To conclude, secondary school graduates, living in regions where the elasticity to fees is high, have a higher degree of flexibility in their choices because of the large number of universities located in neighbor regions and at a reasonably small distance from their residence. They are, therefore, more sensitive to costs than students who have a lower number of opportunities close to the region they live in. Regional authorities, by fixing grants and by subsidizing housing policies, can therefore affect students' enrollment choices in a measure that depends on "outside" opportunities of the region secondary school graduates come from.

12.6 Final Remarks

The ongoing debate on the Italian HE system raises the issues of low participation and graduation rates well below the OECD average. In particular, the empirical research has looked into the effectiveness of the "3 + 2" university reform, that had also the aim of reducing enrollment costs by shortening the legal length of studies, and into the effect of geographical distance on accessibility and completion.

In this work, we study the relationship between the enrollment decisions of Italian secondary school graduates and the cost of participating in HE. We look into the role of incentives, such as scholarships and the supply of under-priced accommodation. Since in Italy incentives are managed by regional institutes (ERSU), our analyses are developed from a regional perspective.

For the purpose of our analysis, we estimate a conditional logit model for enrollment and university choice of Italian secondary school graduates. We build our analyses on the ISTAT survey of secondary school graduates in 2004 interviewed in 2007 linked with data on institutions characteristics from MIUR.

Our empirical strategy provides us with straightforward post-estimation analyses on three key variables: tuition fees, expected grants, and expected rent, that are the main instruments in the hands of the university and regional management for policy tuning. On average, the elasticity of the probability of enrollment to tuition fees is −0.062, the one to expected grants is 0.028, and the one to expected rent is −0.022. Differences between regions are quite marked: southern regions show lower elasticities, while small central and northern regions the largest ones. Such differences can be explained by the accessibility to more opportunities to substitute the choice of which university to attend.

The results of the conditional logit model estimation also confirm that the geographical distance plays a major role in students' choice between universities: students prefer to enroll in universities close to home, implying that they may settle for choices that do no fit at best their ability and preferences. Other than university attributes, we show that a key role in university choice is played by the socioeconomic conditions of the institution's geographical location, suggesting that the process of choosing a university may hide the search for better opportunities.

To conclude, enrollment costs and incentives do affect HE choices of Italian secondary school graduates. As most of direct and indirect costs, such as fees and moving/commuting costs, are sustained by the students' families, individual inequalities may be reduced by the financial aid and facilitation managed by the regional governments.

Appendix (Fig. 12.3; Tables 12.5, 12.6, 12.7 and12.8)

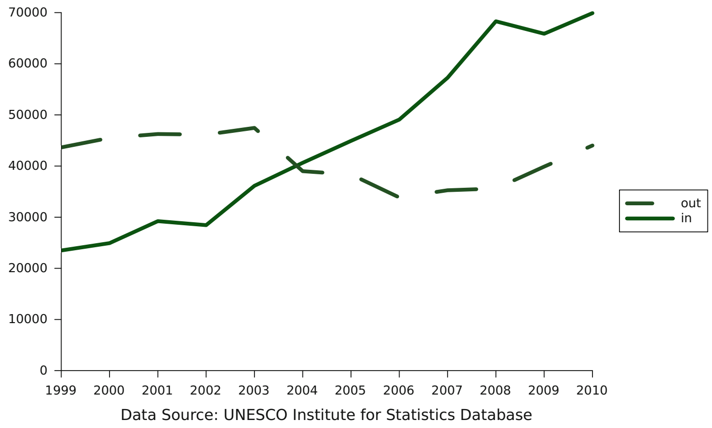

Fig. 12.3 The number of foreign students enrolled in Italy (in) and the number of Italian students enrolled abroad (out): 1999–2010

Table 12.5 Enrolments in universities located in the students' region of residence (1) and enrolments in regional universities of students coming from other Italian regions (2)

	(1)		(2)	
Italian Regions	%	Freq.	%	Freq.
Abruzzo	79.6	623	25.7	668
Basilicata	31.4	477	11.2	169
Calabria	67.6	707	03.6	496
Campania	87.0	811	12.2	804
Emilia-Romagna	91.3	962	39.4	1,449
Friuli-Venezia Giulia	82.6	835	14.7	809
Lazio	92.3	807	39.0	1,221
Liguria	83.5	939	06.1	835
Lombardia	88.2	1,178	31.2	1,511
Marche	74.6	567	15.7	502
Molise	52.1	478	7.1	268
Piemonte	83.1	952	22.2	1,017
Puglia	74.5	737	13.1	632
Sardegna	86.8	570	1.0	500
Sicilia	89.3	759	9.6	750
Toscana	90.6	599	31.1	788
Trentino-Alto Adige	60.8	1,102	6.7	718
Umbria	80.8	448	22.5	467
Valle d'Aosta	21.1	284	6.2	64
Veneto	77.6	1,073	32.8	1,240
Sample	77.9	14,908	22.1	14,908

Column (1): 100 the students participating in higher education in that same region
Column (2): 100 the students enrolled in that same region

Table 12.6 Attractiveness of Italian Regions

Italian Regions	2001	2002	2003	2004	2005	2006	2007
Abruzzo	0.76	0.72	0.82	1.07	1.39	1.86	2.17
Basilicata	0.25	0.25	0.25	0.27	0.27	0.27	0.25
Calabria	0.10	0.08	0.07	0.09	0.08	0.09	0.10
Campania	0.80	0.66	0.59	0.40	0.39	0.27	0.20
Emilia Romagna	4.29	4.14	4.28	4.21	4.39	3.72	3.46
Friuli Venezia Giulia	2.06	2.39	1.83	1.71	1.56	1.44	1.45
Lazio	2.51	2.71	2.79	2.97	2.41	2.50	2.78
Liguria	0.65	0.55	0.53	0.59	0.67	0.86	0.83
Lombardia	1.92	2.27	2.36	2.33	2.07	2.08	2.09
Marche	1.40	1.45	1.30	1.25	1.27	1.11	1.19
Molise	0.64	0.56	0.42	0.53	0.69	0.68	0.66
Piemonte	0.82	0.83	0.77	0.80	0.74	0.74	0.74
Puglia	0.14	0.15	0.14	0.17	0.18	0.26	0.26
Sardegna	0.05	0.06	0.05	0.05	0.04	0.06	0.06
Sicilia	0.68	0.53	0.53	0.49	0.52	0.55	0.43
Toscana	3.00	2.72	2.85	2.92	2.90	2.78	2.62
Trentino Alto Adige	0.77	0.67	0.69	0.75	0.71	1.17	0.78
Umbria	1.75	2.12	2.09	1.85	1.82	1.81	1.71
Valle D'Aosta	–	0.00	0.01	0.01	0.09	0.22	0.16
Veneto	0.78	0.73	0.83	0.82	0.90	0.82	0.88

Source: MIUR—National Committee for evaluation of the Italian university system http://nuclei.cnvsu.it/2007111111100IMMF/provenienze.html. "Attractiveness" of regional universities: it is the ratio between the share of students enrolled in regional universities coming from outside the region on students enrolled in the region and the share of students enrolled in universities outside the region on enrolled secondary school leavers living in the region

Table 12.7 Students' top choices, by region of residence (row)

Italian Regions	Sample most frequent choices %			
Abruzzo	Abruzzo	Lazio	Em. Rom.	Marche
	79.6	8.83	3.85	3.37
Basilicata	Basilicata	Lazio	Puglia	Campania
	31.4	15.93	14.68	9.64
Calabria	Calabria	Lazio	Sicilia	Em. Rom.
	67.6	9.05	8.77	3.68
Campania	Campania	Lazio	Abruzzo	Basilicata
	87.0	5.45	1.85	1.11
Emilia-Romagna	Em. Rom.	Lombardia	Marche	Veneto
	91.3	4.37	1.25	0.73
Friuli-Venezia Giulia	F.V. Giulia	Veneto	Lombardia	Em. Rom.
	82.6	11.38	4.37	1.44

(continued)

Table 12.7 (continued)

Italian Regions	Sample most frequent choices %			
Lazio	Lazio	Abruzzo	Umbria	Campania
	92.3	2.11	1.98	0.99
Liguria	Liguria	Toscana	Lombardia	Em. Rom.
	83.5	5.22	4.58	2.98
Lombardia	Lombardia	Em. Rom.	Veneto	Piemonte
	88.2	5.69	3.06	0.85
Marche	Marche	Em. Rom.	Lazio	Umbria
	74.6	13.05	4.23	3.17
Molise	Molise	Lazio	Abruzzo	Em. Rom.
	52.1	17.15	14.02	5.02
Piemonte	Piemonte	Lombardia	Liguria	Em. Rom.
	83.1	10.82	4.10	0.42
Puglia	Puglia	Em. Rom.	Abruzzo	Lazio
	74.5	5.83	5.02	3.93
Sardegna	Sardegna	Em. Rom.	Lazio	Lombardia
	86.8	2.98	2.81	2.46
Sicilia	Sicilia	Toscana	Lombardia	Em. Rom.
	89.3	2.24	1.98	1.58
Toscana	Toscana	Umbria	Em. Rom.	Lazio
	90.6	3.51	3.34	0.83
Trentino-Alto Adige	Trentino-A.A.	Veneto	Em. Rom.	Lombardia
	60.8	21.14	7.26	5.99
Umbria	Umbria	Toscana	Em. Rom.	Abruzzo
	80.8	4.46	2.46	1.34
Valle d'Aosta	Piemonte	Valle d'Aosta	Lombardia	Toscana
	51.76	21.13	19.01	2.11
Veneto	Veneto	Em. Rom.	F.V. Giulia	Trentino-A.A.
	77.6	7.83	7.64	2.98

Source: ISTAT, survey on studying and working experiences of secondary school leavers (graduated in 2004, interviewed in 2007). Italian regions that have the highest enrollment rates (columns) by the students region of provenance (row)

Table 12.8 Descriptive statistics for *DISTANCE*, *RANKING*, *QUALITY OF LIFE*, *UNEMPLOYMENT RATE*, *POPULATION*, and *DELAYED GRADUATION* in the Italian macro-areas

Macro-area	Stat.	*DISTANCE*	*RANKING*	*QUAL. OF LIFE*	*UNEMP. RATE*	*POP.*	*DELAYED GRAD.*
North-West	Mean	0.93	8.84	4.71	0.05	1.99	0.24
	Min	0.00	7.66	4.19	0.03	0.01	0.03
	Max	15.59	10.08	5.06	0.06	3.16	0.45
	Sd	2.06	0.48	0.28	0.01	1.03	0.12
Nord-East	Mean	1.02	9.13	4.77	0.04	0.65	0.32
	Min	0.00	8.55	4.30	0.04	0.04	0.14
	Max	14.22	10.13	5.07	0.06	0.99	0.46
	Sd	1.84	0.46	0.26	0.01	0.30	0.06
Center	Mean	1.40	8.96	4.58	0.06	1.92	0.35
	Min	0.00	7.90	3.88	0.03	0.21	0.16
	Max	13.04	10.30	4.99	0.11	4.19	0.45
	Sd	2.16	0.49	0.34	0.01	1.76	0.05
South	Mean	0.48	8.56	3.88	0.13	1.08	0.37
	Min	0.00	6.83	3.44	0.06	0.03	0.23
	Max	13.22	9.83	4.40	0.19	3.08	0.54
	Sd	0.93	0.60	0.28	0.04	1.04	0.10
Islands	Mean	0.46	8.75	3.77	0.17	0.71	0.41
	Min	0.00	8.23	3.43	0.05	0.06	0.33
	Max	11.85	9.50	4.99	0.20	1.25	0.49
	Sd	0.88	0.36	0.32	0.02	0.49	0.05
Total	Mean	0.92	8.88	4.47	0.07	1.31	0.33
	Min	0.00	6.83	3.43	0.03	0.01	0.03
	Max	15.58	10.30	5.07	0.20	4.19	0.54
	Sd	1.79	0.53	0.49	0.05	1.21	0.10

Distance, traveled by the students enrolled in universities located in the macro-areas, is in 100 km. Population is in millions of people

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Chapter 13
Globalized Markets, Globalized Information, and Female Employment: Accounting for Regional Differences in 30 OECD Countries

Justina A.V. Fischer

Abstract Accounting for within-country spatial differences is a neglected aspect in many cross-country comparisons. This chapter highlights this importance in this empirical analysis of the impact of a country's degree of informational and economic globalization on female employment in 30 OECD countries, using a micro pseudo panel of 110,000 persons derived from five waves of repeated cross sections from the World Values Survey, 1981–2008. I conjecture that informational globalization affects societal values and perceived economic opportunities, while economic globalization impacts actual economic opportunities. A traditional cross-country analysis suggests that the informational dimension of globalization but not the economic one increases the probability of employment for women—contradicting the Becker (1957) hypothesis of international competition mitigating discrimination in employment. However, accounting for subnational regional gender heterogeneity reveals that the impact of worldwide information exchange works rather at the regional level, while economic globalization (trade) increases female employment in general.

Keywords Globalization • Economic integration • Labor market • Employment • Regions • Social norms • Communication • Discrimination • Gender • World values survey

JEL Classification C33, D83, F14, F16, F66, J16, J71, R23, Z13

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13.1 Introduction

Women's employment is a debated topic in economics and in the public, particularly since it has become evident that an ordinary family profits from women's contributions to household resources. In addition, the welfare state might also profit from increased female employment: in times of growth volatility and higher job turnover, female employment might reduce men's demand for automatic macroeconomic stabilizers and reduce social transfers (e.g., EU 2010). According to Becker (1957, 1971), if nonparticipation and nonemployment of women are a result of their discrimination in the domestic labor market, a country's exposure to global competition through imports, exports, and FDI should mitigate this phenomenon: more women are predicted to be working as a country opens up to world markets. In addition, I conjecture that the exchange of information around the world might lead to self-criticism and reassessment of cultural traditions, such as the traditional role model that attributes to men the role of sole breadwinner in the family. Additionally, the worldwide exchange of information may also affect how women perceive their occupational "choice set" and their resulting labor supply decisions. For this reason, greater exposure to worldwide information flows should equally lead to more women participating in the labor market.

This article empirically investigates the impact of globalization on female labor market participation and female employment in OECD countries; this study employs "globalization" in two of its manifestations: first, in the form of a country's economic integration into global markets ("economic globalization") and second, in the form of worldwide information exchange between people through tourism and the internet ("informational globalization"). This empirical analysis of globalization effects for female employment focuses on two questions: (1) to what extent does each country's global integration lead to more women in paid employment and (2) are there within-country spatial differences in these globalization effects. I employ a micro pseudo panel—a collection of repeated cross sections of individual-level survey data—for 30 OECD countries using 110,000 observations of the World Values Survey from 1981 to 2008, which I match with indicators of a country's economic and informational openness developed by the KOF (Technical University of Zurich); the variations of such indicators across time and space allow for the identification of globalization effects. The World Values Survey also contains information on the subnational region where the interview had been conducted, which I use for investigating regional differences.

Previous empirical studies on the effects of international trade for women's labor market participation suffer from being case studies for single countries only; they have revealed mixed evidence for developing and developed countries, for the type of sectors affected and for the production technology employed (see also Lee 2005). Nordas (2003) compares in her case study Mauritius, Mexico, Peru, the Philippines, and Sri Lanka; international trade appears to have created jobs for women, particularly in the exporting sector (see also Nowbutsing and Ancharaz 2011). Irrespective of heterogeneous wage level effects, case studies for Bangladesh, Madagascar, Turkey, and Tunisia equally show that female employment in the formal sector rose (Fontana and Wood 2000; Glick and Rouaud 2004; Haouas et al 2003; Ozler 2000). Also, Cagatay and Berik (1990), Joekes and Weston (1994), and Aguayo-Tellez et al. (2010) showed increased female employment for Turkey and Mexico as a consequence of trade liberalization, as do Giddis and Pieters (2012) for Brazil. Contrasting evidence is reported for the OECD member state Mexico by Sauré and Zoabi (2009) who show decreased female employment; they argue that in the contracting sector male workers were laid off who then replaced female workers in the exporting sector, which is originally female-labor intensive. Similarly, negative employment effects for women have been revealed by Al Azzawi (2013) for Egypt, and Kucera (2001) and Kongar (2005) for Germany, Japan, and the USA.

The contribution of this article to the existing literature is twofold: first, this study defines globalization not only in terms of international exchange of goods and cross-national transfers of money but also in terms of exposure to worldwide information flows. Second, this chapter makes an attempt to take account for regional heterogeneity in a thorough manner: Spatial variation within countries exists not only with respect to local culture and institutions but also industry structures; consequently, globalization may well exert differential impacts depending on the subnational region the respondent lives in. In contrast to most previous cross-country studies, this regional differentiation in my empirical approach is only possible because the analysis I use exploits individual-specific information around the world.

My results show clearly how important it is not to neglect spatial differences and to differentiate between transmission channels when investigating globalization effects. The first set of cross-country estimations suggest that worldwide information flows between people and cultural exchange increase the employment probability of women, while economic integration as such does not appear to exert such gender-specific effects. Contrasting results are obtained for the second set of estimations for which I assume that gender effects differ by regions: now it is economic integration but not information exposure that appears to raise female labor market activity. Overall, both informational and economic globalization appear to increase labor market participation of women, with the transforming forces of informational globalization working more at the regional level and those of economic globalization more at the national level.

This chapter is organized as follows: the next section derives from relevant literature testable hypotheses on economic and informational globalization and female employment. Section 13.3 describes the data, while Sect. 13.4 introduces the empirical model. Section 13.5 presents the basic results, while Sect. 13.6 pays particular attention to spatial differences. Section 13.7 concludes the chapter.

13.2 Hypotheses

Empirical studies on the impact of trade and FDI on labor markets are manifold—most of them find a positive effect on general employment, particularly in cities (for a trade literature review, see Fischer 2012a; for more spatial approaches, see Pastore and Ferragina 2008). Female participation in the labor market might be enhanced by foreign trade for several reasons: first, in the domestic goods markets, trade might add a foreign demand to the already existing domestic demand so that more workers need to be employed, with female workers being drawn overproportionally, who had been largely occupied with household production before the country opened up (for empirical evidence, see Ozler 2000). Second, Becker (1957, 1971) predicts that international competition forces firms to produce at efficient costs, making them act less discriminatory toward employing women by choosing any worker suited best for a position. However, Busse and Spielmann (2006) provide empirical evidence that, when facing fierce international competition, domestic firms substitute expensive male workers with female laborers who are less costly (as a result of their discrimination). Finally, international trade theory conjectures that economic integration generates technological spillovers across countries—progress in household production technology, however, reduces the opportunity (time) costs for female employment (e.g., Goldin 2006).

However, not only economic integration but also the worldwide flow of information on foreign cultures and values might play a decisive role for female labor market participation and employment; obtaining information about other countries through media and travel implies exposure to alien societies and values that challenge one's own beliefs and convictions (e.g., Huntington 1996). Possibly, such exposure to alternative ways of living and philosophies aids women in finding new idols for identification, expanding their subjective set of economic opportunities, and helps them in overcoming the traditional role model. Based on these arguments, I can establish the following testable hypothesis:

Hypothesis 1 Not only economic integration but also informational globalization increases women's labor market participation and employment probabilities.

An important contribution of this chapter lies not only in differentiating between the economic and other societal dimensions of globalization but also in taking into account within-country spatial heterogeneity. Previous studies on trade effects for labor markets combine aggregate measures of trade with aggregate measures of unemployment, neglecting regional effects (e.g., Felbermayr et al. 2011). Such studies, albeit being the current standard, assume implicitly that countries are homogeneous across subnational regions in their economic and social structures. Those regional differences in social norms, industrial structures, and production technologies (both at home and in manufactures) play a role for female labor market participation which has been suggested by various authors (e.g., Goldin 2006; Goto 2006; Pastore and Tenaglia 2013). For example, Munshi and Rosenzweig (2006) have shown that men and women in India react in their schooling choices completely differently to globalization, while Bettio et al. (2012) reveal that men and women in Europe show partly different reactions to the current economic crisis. Thus, I conjecture that the employment effects of globalization are, again, not only different between men and women but also across regions—I also assume that such gender heterogeneity equally differs across regions. Hence, the second hypothesis could be formulated as:

Hypothesis 2 The impact of globalization on female employment is different across subnational regions.

13.3 Data

This study employs the World Values Survey (2013), 1981–2008, an international survey that has collected in five waves, individual-specific information on 340,000 persons; pooling these five waves of individual cross-sectional data into one micro-sample yields a so-called "micro pseudo panel" where an unbalanced panel structure emerges at the country level. This data set includes respondents' employment status, age, gender, household income, education and marital status, the year of the interview, and the country of residence. Information on the subnational region where the interview was conducted is available for about 80 % of interviewees, and, on average, each country was divided in about 10 regions. Labor market participation ("active") is defined as being "employed" or being "unemployed," that is actively seeking a paid position; "inactive" persons include then housewives and early retired. As "employed" are defined as persons with either a full-time position, a part-time position, or who are freelancers; the comparison group is then not only the officially recorded unemployed but also housewives and early retired persons—"housewives" and "early retired" are still marginally attached to the labor market and close to entering. The analysis is restricted to the group of persons who can be expected to be active in the labor market—that is, 18–60 years old. Overall, I have excluded pupils at schools, students at universities, old-aged persons, and disabled persons, yielding a world sample of 264,000 persons. Altogether, the sample of suitable interviewees in OECD countries that are used in this analysis amount to about 110,000 persons in 30 countries; about 50 % of the interviewees are female and about 70 % are employed (see also the summary statistics in Table 13.1). For about 18,800 observations in the OECD sample, no information on region of residence is available. There are about 630 coded regions in the data; I exclude regions with less than 15 observed persons to avoid multicollinearity; about 570 regions remain. The panel structure at the country (regional) level, in combination with the individual-specific information available in the form of repeated cross sections, allows me to build a micro pseudo panel.

To account for the degree of globalization, I employ two measures: the KOF index of economic globalization and the KOF index of informational globalization (see Dreher et al. 2008). Both indices range from 0 (complete isolation) to 100

Table 13.1 Descriptive statistics of main variables (106,648 observations)

Variable	Mean	Std. Dev.	Min.	Max.
Active	0.80	0.40	0	1
Employed	0.73	0.44	0	1
Unemployed	0.07	0.25	0	1
Economic globalization	69.14	13.48	28.45	97.51
Economic glob. (log)	4.22	0.21	3.35	4.58
Informational globalization	69.03	14.67	37.27	90.23
Info. glob. (log)	4.21	0.24	3.62	4.50
Female	0.52	0.50	0	1
Age	38.44	11.59	18	60
Year of survey	1994.59	7.58	1981	2008

(complete openness). The index of economic globalization measures a country's exposure to the global economy; this index is based on national statistical information mainly on volumes of exports, imports, and FDI. The index of informational globalization reflects a country's degree of exposure to the worldwide flow of information: it is based on national statistics of travel activity, flows of tourists, exposure to the US culture, media consumption, and Internet diffusion (see also Table 13.6). Employed in their log forms to account for a decreasing marginal impact as globalization rises, the correlation coefficient of economic and informational globalization is 0.75 in the full sample and 0.76 in the regional sample. These moderate correlations allow the separate identification of the two dimensions of globalization. Both measures show sufficient variation across countries and time (see also Fischer and Somogyi 2012). The KOF index of globalization is the most widely employed measure of globalization and has been used in more than 100 papers of the recent economic literature (e.g., Potrafke 2013, 2014; Berggren and Nilsson 2014; Fischer 2012b, c).

Table 13.1 provides summary statistics of the variables and measures employed in the empirical analyses. In the pooled sample, there are 110,253 persons, out of which 52.5 % are female. Of the 106,648 persons whose occupational status is known, 72.8 % are recorded as employed, 79.8 % are reported active, while the difference of 6.9 % represents the group of unemployed persons. In absolute numbers, most regression samples utilize about 77,700 employed, 7,400 unemployed, and 21,500 persons who are out of the active population for reasons described above. The measures of informational and economic globalization show similar characteristics in their distributions but are correlated only with 0.75 (see also above).

13.4 Methodology

The empirical analysis estimates Logit regressions on the probability of being gainfully employed compared to not being employed and the likelihood of participating in the labor market ("active") compared to being "inactive" in the labor market, respectively, where being "active" includes both employed and unemployed persons (see also Sect. 13.3).

The focal variables are the two measures of economic and informational globalization; in order to account for their female labor participation effects, these two globalization measures have been interacted with the respondent's gender.

The baseline specification takes the following form:

$$y_{its} = \alpha + \beta \text{ globalization}_{ts} + \gamma \text{ female}_{its} + \text{globalization}_{ts} \times \text{female}'_{its}\delta + X'_{its}\zeta + FE_t + FE_s + \varepsilon_{its}$$

Where y_{its} is a dichotomous indicator of labor market participation of individual i in year t in country s. Respondent i's gender at year t in country s (female_{its}) and $\text{globalization}_{ts}$ in country s at year t are both estimated as direct effects determining individual i's labor market participation. In addition, the coefficient on their interaction term ($\text{globalization}_{ts} \times \text{female}_{its}$) is estimated—it is this interaction term I am particularly interested in.

FE_t and FE_s represent sets of country- and time-specific fixed effects that control for unobserved shared national characteristics such as culture and history but also global financial market shocks. In the estimations, wave fixed effects account for these unobservable time fixed effects. In the case of stable OECD countries, country fixed effects also account for population size and political institutions. X_{its} includes (nonlinear) age as individual-specific control, and ε_{its} is an error term clustered within country-years—cluster standard errors are robust to arbitrary heteroskedasticity and arbitrary intra-group correlation. Logit estimations yield coefficient vectors β and δ that represent the direction of these globalization effects.

Further model extensions include adding a set of individual-specific predictors of employment to X_{its} in order to include household income, educational attainment, and marital status, which could all be impacted by globalization; interacting country fixed effects with time fixed effects ($FE_t \times FE_s$) allows to control for unobservable within-country changes of either institutions or the macroeconomic state.

Without instrumenting globalization or exploiting a quasi-natural experiment setting, causality is derived from the inclusion of country-specific and time-specific fixed effects (and their interactions) only. On the other hand, the idea of a reversed causality appears rather unrealistic: in that case, increased domestic (female) labor market participation should have triggered the economic need of, and political demand for, more international trade.

13.5 Findings

Table 13.2 presents the results for the impacts of economic globalization and informational globalization on the probability for women to be employed or to be actively participating in the labor market, as compared to men—this gender-specific heterogeneity of globalization effects is reflected by the two interaction terms. Columns 1 and 2 present the estimates of the baseline model—column 1 for employment and column 2 for labor market participation. Columns 3 and 4 repeat this analysis but add marital status, household income, and educational attainment as socio-demographic controls to the baseline model, considerably improving the model fit as measured by the Pseudo R2s. Unobserved changes in institutions or economic development are accounted for by interacting country fixed effects with time fixed effects in columns 5 and 6. (Results for the control variables are reported in Table 13.7.) The estimated coefficients of the two interaction terms ("economic globalization × female" and "informational glob. × female") appear robust to these alterations in model specification.

Table 13.2 reveals that globalization effects differ across gender—but only for informational globalization, as its significant interaction term estimate with gender indicates: as a country becomes more exposed to worldwide flows of information and cultural exchange, the probability of being active in the labor market and working in gainful employment increases for women over men, all other things being equal. This finding is consistent with my hypothesis of changes in social norms or in individual's perceived occupational choice set which is triggered by inflowing information about alien countries and cultures, putting the traditional values and perceptions into question.

In contrast, classical economic integration does not affect employment probability or labor market participation likelihood of women as compared to men—contradicting the Becker (1957) hypothesis of a discrimination-alleviating effect of economic integration. The absence of a female employment increasing influence of economic globalization (international trade) in developed countries has already been reported by Wood (1991, 1994).

Table 13.2 also reveals some additional information: women appear, in general, less likely to be active or employed than men, either caused by the traditional role model or caused by periods of motherhood. Based on column 3 of Table 13.2, the estimated probability of employment for women at sample mean age of 38 years is 60.68 % (men: 85.8 %). The picture for women changes, however, with her age: at the age of 30 through 40, a woman's predicted probability of being employed is about 65 %, while at the age of 40 and 59, she shows a lower estimated likelihood of 59 % and 36 %, respectively. In contrast, between 30 and 60 years of age, men reveal consistently higher predicted probabilities of being employed than women: at ages 30 through 50 years, likelihoods range between 85 % and 89 %, and at the age of 59, the estimated probability is still 69 %.

Coefficients on interaction terms between gender and globalization indicate only directions of influence—these are more meaningfully interpreted as marginal

Table 13.2 Globalization and female employment in 30 OECD countries, 1981–2008

	(1)	(2)	(3)	(4)	(5)	(6)
	Employed	Active	Employed	Active	Employed	Active
Female	−10.858***	−13.257***	−11.565***	−14.229***	−11.847***	−14.459***
	(1.269)	(2.253)	(1.371)	(2.434)	(1.377)	(2.500)
Female × econ. glob. (log)	0.091	−0.219	−0.036	−0.320	0.056	−0.301
	(0.458)	(0.831)	(0.472)	(0.865)	(0.469)	(0.898)
Female × info. glob. (log)	2.102***	2.765***	2.396***	3.087***	2.369***	3.119***
	(0.342)	(0.568)	(0.369)	(0.590)	(0.376)	(0.613)
Econ. glob. (log)	−0.320	−0.313	0.049	0.003	−3.606***	−2.681***
	(0.492)	(0.783)	(0.603)	(0.814)	(0.427)	(0.841)
Info. glob. (log)	−2.312***	−3.131***	−1.980***	−3.017***	8.550***	12.846***
	(0.414)	(0.546)	(0.418)	(0.611)	(0.997)	(1.337)
Age	Yes	Yes	Yes	Yes	Yes	Yes
Household income, marital status, education	No	No	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE × Wave FE	No	No	No	No	Yes	Yes
Obs.	102,947	102,947	102,609	102,609	102,609	101,875
Countries	30	30	30	30	30	30
Clusters	102	102	102	102	102	101
Pseudo R^2	0.1696	0.2768	0.2218	0.3313	0.2300	0.3359

Notes Logit estimations with standard errors clustered at the country-year level. Analysis is restricted to the age group of the 18–60-year-old. “Employed” refers to doing full-time employment, part-time employment, or freelance work, with unemployed, housewives/housemen, and early retired serving as comparison group. “Active” includes both employed and unemployed. “***”, “**” and “*” indicate statistical significance at the 1, 5 and 10 percent levels, respectively. Complete results are reported in Table 13.7. Estimated with Stata 13

Table 13.3 Predicted employment probabilities for men and women

Economic glob. (log)	Men (%)	Women (%)	Info. glob. (log)	Men (%)	Women (%)
2	84.71	60.14	2	99.72	42.38
3	85.24	60.38	3	98.10	50.75
4	85.77	60.63	4	89.40	59.05
5	86.28	60.87	5	61.98	66.87

Notes Measured at respondents' mean age of 38 years. Based on column (3) of Table 13.2

effects of gender on employment probabilities as a country opens up to the world; Table 13.3 derives the gender-specific changes in predicted employment probabilities from the estimated model in column 3 of Table 13.2 (Qualitatively identical results based on column 1 of Table 13.2 are reported in Table 13.8). Let me first start with economic globalization, whose interaction term with gender showed no significant impact on employment (see Table 13.2). Starting with a minimum level of economic globalization (in log-form) of two points, that I let increase until the maximum of five points, evaluated at their mean ages of 38 years, predicted employment probabilities of both men and women appear to stay constant—for men at roughly 85 % and for women at about 60 %. Thus, I conclude: as economic globalization increases, the odds for being employed of women relative that of men remain unaffected.

The picture for informational globalization is different; evaluated at respondents' mean age of 38, predicted employment probabilities for women increase continuously as information flows across countries intensify; at the minimum of informational globalization (log) of two points, female employment probability is 42.4 %, while at its maximum of five points, employment probability for women has increased by 50–66.9 %. In contrast, at lower levels of informational globalization, the employment likelihood for men stays largely unaffected (99–89 %), while at higher levels, it falls down to 62 %, even below the female level of 67 %. In sum, predicted employment likelihoods for women rise relative to those for men as national exposure to cross-cultural contacts intensifies.

Altogether, the marginal effects analysis of Table 13.3 suggests that informational globalization increases female labor market participation and employment probability compared to that of men. While predicted probabilities for women significantly rise, those for men tend to fall, possibly indicating a substitution of male labor for female one, in support of Busse and Spielmann (2006). In the next section, I will analyze to what extent differences in gender across subnational regions might drive these results.

13.6 Regional Differentiation

In order to understand to what extent there are within-country spatial differences with respect to the above-described employment effects of globalization for women, Table 13.4 adds varying sets of interaction terms that account for different forms of

Table 13.4 Globalization and female employment in 30 OECD countries, 1981–2008: accounting for regional differences

	(1) Employed	(2) Employed	(3) Employed
Female	−1.762***	−1.771***	−2.127***
	(0.247)	(0.246)	(0.551)
Female × econ. glob.	−0.0785	−0.0771	0.378*
	(0.0961)	(0.0960)	(0.206)
Female × info. glob.	0.434***	0.434***	0.0747
	(0.0896)	(0.0897)	(0.297)
Econ. glob. (log)	−0.210**	−0.714	4.751*
	(0.0955)	(0.637)	(2.817)
Info. glob. (log)	1.671***	−32.13***	−17.61**
	(0.220)	(1.312)	(7.137)
Way of accounting for regional differences	Wave FE × region FE	As in model (1) plus globalization × region FE	As in model (2) plus female × region FE
Age	Yes	Yes	Yes
Household income, marital status, education	No	No	No
Country FE	No	No	No
Region FE	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes
Region FE × wave FE	Yes	Yes	Yes
Country FE × wave FE	No	No	No
Obs.	84,683	84,683	84,683
Countries	30	30	30
Country-years	88	88	88
Adjusted R^2	0.193	0.193	0.208

Notes OLS estimations with standard errors clustered at the country-year level. T-statistics in parentheses. Prior to running the regressions, regions with less than 15 observations have been excluded. Analysis is restricted to the age group of 18–60-year-old. "Employed" refers to doing full-time employment, part-time employment, or freelance work, with unemployed, housewives/housemen and early retired serving as comparison group. "***", "**" and "*" indicate statistical significance at the 1, 5 and 10 percent levels, respectively. Estimated with Stata 13

within-country regional heterogeneity. Column 1 of Table 13.4 replicates column 1 of Table 13.2, accounting for unobserved heterogeneity at the regional level, now using region fixed effects in place of country fixed effects and their interaction terms. "Region" is recorded in the World Values Survey as "the region where the interview is conducted," resulting in more than 630 entities (see Sect. 13.3). In most countries, these regions are politically defined, reflecting "states" or "departments."

Possibly, these regions differ with respect to the structures of their economies: some regions might have a large resource extraction industry, others might export mainly agricultural goods, while, again, others might specialize in providing financial services. Therefore, column 2 tests the idea that general globalization effects for employment are heterogeneous across subnational regions; specifically, column 2 tests for informational and economic globalization effects in regions by adding interaction terms between region fixed effects and the corresponding two indices of globalization. Obviously, taking account of spatially differential effects of globalization supports the previous findings of Table 13.2: informational globalization increases women's employment probabilities over men's, while the gender-specific impact of economic globalization remains negligible.

Column 3 goes one step further by assuming that the specific impact of globalization on female employment might equally depend on the region the affected woman lives in: Regions differ not only with respect to the structure of the economy (see above) but also with respect to culture and institutions. Pastore and Tenaglia (2013) have shown that personal religious beliefs determine labor market participation decisions of women, while Munshi and Rosenzweig (2006) suggest that women and men react to a globalizing economy in different ways. Consequently, people's values and economic structures in regions might play an important role in how globalization impacts women compared to men.

To account for these regional differences, column 3 adds to the previous specifications, the interaction terms of "female" with "region fixed effects." Now, I observe a switch in the results: at the (cross-)country level, the female employment effect appears now entirely driven by economic globalization (significance at the 10 % level), while informational globalization plays no decisive role. Obviously, the impact of informational globalization on female employment takes place at the regional level and is taken account of by addressing regional heterogeneity of women's reaction to globalization. However, because of possible quasi-multicollinearity in the model specification between region fixed effects and their interactions with gender and globalization, this result needs to be taken *cum grano salis*, calling for more in-depth research on regional heterogeneity of globalization effects using more refined data.

An issue of concern is that certain countries might drive our empirical findings; for example, some of the more recent OECD member states experienced a decisive increase in their exposure to global markets, resulting in a sharp increase in the respective globalization indices I employ. A related concern is that certain years or time periods might be particularly influential. The presence of influential countries or time periods would cast doubt on the generality of the estimates presented before. Table 13.5 tests the sensitivity of the main findings of column 3 of Table 13.2 with respect to, first, single countries and, second, waves of the World Values Survey; the five waves cover roughly the periods 1980–1985, 1990, 1995–1997, 2000, 2005–2008. Overall, the main findings appear robust.

Table 13.5 Robustness test

	Sensitivity to single country	Sensitivity to single wave
Female		
Min	−10.94***	−13.65***
	(1.254)	(1502)
Max	−12.85***	−10.82***
	(1.269)	(1.418)
Female × econ. glob. (log)		
Min	−0.190	−0.614
	(0.577)	(0.502)
Max	0.983	0.297
	(0.495)	(0.542)
Female × info. glob. (log)		
Min	2.187***	1.984***
	(0.436)	(0.461)
Max	2.651***	2.815***
	(0.344)	(0.380)

Note Model of column 3 in Table 13.2 estimated with Logit. Dependent variable: "being employed". "***", "**" and "*" indicate statistical significance at the 1, 5 and 10 percent levels, respectively

13.7 Conclusion

Most empirical studies on the employment effects of economic integration suffer from two shortcomings: first, most studies neglect that worldwide integration goes beyond pure exchange of goods, services, and money; growing cross-country linkages also transport information about foreign people, societies, and cultures. Second, most studies are for single countries only, neglecting aspects of cross-country comparisons. The present empirical analysis of the impact of economic and informational globalization on female employment in 30 OECD countries tries to remedy both shortcomings.

Using occupational information on 110,000 persons in 30 OECD countries between 1981 and 2008 obtained from the World Values Survey, I construct a micro pseudo panel that I match with measures of informational and economic globalization at the country level—individual's employment probabilities are estimated with Logit. Causal inference is made through the inclusion of two-way fixed effects and their interactions at the country or regional level.

My results show that there are two channels of globalization at work that exert differential effects; in addition, the modeling of subnational regional structure appears to influence how the impact of economic and informational globalization on female employment becomes evident. The traditional empirical model that exploits cross-country variation only indicates strongly that worldwide information flows bear the main effect for the higher employment probability of women as compared to men; in contrast, international trade does not appear to exert such gender-specific employment effect. This finding contradicts the traditional Becker hypothesis of discrimination alleviation that is triggered by competitive pressure through globalized markets only. However, when assuming that gender-specific responses differ by subnational region, the results for the national level reveal a tendency that solely economic globalization raises female employment, while informational globalization exerts no such effect. It can be concluded that the impact of informational globalization for women works rather at the regional level. These heterogeneous findings when varying between regional and national models of globalization effects do not have to be regarded as contradicting each other—on the opposite, they might complement each other.

One possible interpretation of my findings is that both informational and economic dimensions of globalization increase female employment, one working at the regional level, the other one at the national level. Economic globalization might relate to increased demand for female laborers through international trade, manifesting at the national level. In contrast, the transforming forces of informational globalization through the inflow of foreign values and cultures possibly relate to changes in social norm and/or perceived economic opportunities—such changes, however, are likely to occur with some differences across subnational regions. I leave this particular question of differentiating between social norm change and occupational choice set change to future research. Overall, this chapter delivers important insights that bear considerable implications for social and economic policies aiming at societal changes: such policies might be more effective when taking account for spatial differences, when being decided on and implemented at the regional level.

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Appendix

Qualitatively, a marginal effects analysis for the baseline model in column 1 of Table 13.2 in the main text yields identical results as the marginal effects reported in Table 13.3 of the main text. For reasons of completion, Table 13.8 is briefly discussed here: In the case of economic globalization we observe that predicted employment probabilities of both men and women fall; however, the difference in employment probability across gender remains roughly constant. Thus we can conclude: as economic globalization increases, relative employment probability for women is not changed.

Table 13.6 Composition of economic and informational globalization indices

Indices and variables	Weights (%)
Economic globalization	**36**
(i) Actual flows	(50)
Trade (percent of GDP)	(21)
Foreign direct investment, stocks (percent of GDP)	(28)
Portfolio investment (percent of GDP)	(24)
Income payments to foreign nationals (percent of GDP)	(27)
(ii) Restrictions	(50)
Hidden import barriers	(24)
Mean tariff rate	(27)
Taxes on international trade (percent of current revenue)	(26)
Capital account restrictions	(23)
Social [Informational] globalization	**37**
(1) Data on personal contact	(34)
Telephone traffic	(25)
Transfers (percent of GDP)	(4)
International tourism	(26)
Foreign population (percent of total population)	(21)
International letters (per capita)	(25)
(2) Data on information flows	(35)
Internet users (per 1,000 people)	(33)
Television (per 1,000 people)	(36)
Trade in newspapers (percent of GDP)	(32)
(3) Data on cultural proximity	(31)
Number of McDonald's restaurants (per capita)	(44)
Number of Ikea (per capita)	(45)
Trade in books (percent of GDP)	(11)

Source KOF Globalization index (2012). http://globalization.kof.ethz.ch/

In the case of informational globalization, however, the decline in employment likelihood is asymmetric across gender: this decline occurs more rapidly for men than for women. At the minimum of informational globalization employment probabilities are 99.8 % for men and 68.6 % for women, while at its maximum employment probabilities have almost equalized (55.3 % vs. 56.8 %). In sum, when informational globalization gains momentum predicted employment likelihoods fall much faster for men than for women; put differently, relative to men, women gain in employment probability as national exposure to cross-cultural contacts intensifies.

Table 13.7 Complete estimation results

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Employed	Active	Employed	Active	Employed	Active
Female	−10.858***	−13.257***	−11.565***	−14.229***	−11.847***	−14.459***
	(1.2695)	(2.2530)	(1.3707)	(2.4341)	(1.3775)	(2.5005)
Female × econ. glob.(log)	0.091	−0.219	−0.036	−0.320	0.056	−0.301
	(0.4579)	(0.8311)	(0.4722)	(0.8649)	(0.4691)	(0.8984)
Female × info. glob.(log)	2.102***	2.765***	2.396***	3.087***	2.369***	3.119***
	(0.3422)	(0.5685)	(0.3692)	(0.5900)	(0.3757)	(0.6126)
Econ. Glob. (log)	−0.320	−0.313	0.049	0.003	−3.606***	−2.681***
	(0.4925)	(0.7830)	(0.6030)	(0.8140)	(0.4269)	(0.8406)
Info. Glob. (log)	−2.312***	−3.131***	−1.980***	−3.017***	8.550***	12.846***
	(0.4142)	(0.5457)	(0.4184)	(0.6108)	(0.9971)	(1.3367)
Age	−0.245***	−0.827***	−0.174***	−0.512***	−0.179***	−0.526***
	(0.0562)	(0.0794)	(0.0556)	(0.0804)	(0.0552)	(0.0802)
Age^2/100	0.813***	2.176***	0.659***	1.494***	0.673***	1.529***
	(0.1478)	(0.2071)	(0.1468)	(0.2094)	(0.1458)	(0.2090)
Age^3/10,000	−0.870***	−1.932***	−0.749***	−1.440***	−0.761***	−1.469***
	(0.1235)	(0.1713)	(0.1230)	(0.1729)	(0.1224)	(0.1727)
Elementary			−0.358***	−0.349***	−0.450***	−0.429***
			(0.0526)	(0.0628)	(0.0440)	(0.0582)
Secondary	Reference	Category				
Tertiary			0.572***	0.573***	0.573***	0.577***
			(0.0406)	(0.0636)	(0.0425)	(0.0640)
Married/cohabiting	Reference	Category				

Divorced			0.573***	1.136***	0.591***	1.157***
			(0.0658)	(0.0781)	(0.0650)	(0.0761)
Separated			0.449***	1.031***	0.471***	1.058***
			(0.0808)	(0.1167)	(0.0787)	(0.1127)
Widowed			0.299***	0.519***	0.308***	0.534***
			(0.0875)	(0.0956)	(0.0880)	(0.0951)
Single			0.614***	1.820***	0.611***	1.821***
			(0.0569)	(0.0871)	(0.0560)	(0.0860)
Income cat. 1	Reference	Category				
Income cat. 2			0.512***	0.133	0.500***	0.121
			(0.0726)	(0.0890)	(0.0721)	(0.0865)
Income cat. 3			0.865***	0.418***	0.869***	0.399***
			(0.0844)	(0.0749)	(0.0875)	(0.0779)
Income cat. 4			1.194***	0.625***	1.234***	0.630***
			(0.0968)	(0.0794)	(0.0945)	(0.0781)
Income cat. 5			1.367***	0.810***	1.396***	0.826***
			(0.0995)	(0.0717)	(0.1003)	(0.0722)
Income cat. 6			1.631***	1.020***	1.657***	1.041***
			(0.1133)	(0.0923)	(0.1152)	(0.0919)
Income cat. 7			1.778***	1.135***	1.815***	1.172***
			(0.1162)	(0.0935)	(0.1174)	(0.0929)

(continued)

Table 13.7 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Employed	Active	Employed	Active	Employed	Active
Income cat. 8			2.001***	1.324***	2.054***	1.376***
			(0.1243)	(0.1040)	(0.1253)	(0.1015)
Income cat. 9			2.092***	1.441***	2.157***	1.509***
			(0.1259)	(0.1109)	(0.1264)	(0.1061)
Income cat. 10			2.204***	1.520***	2.253***	1.588***
			(0.1416)	(0.1287)	(0.1386)	(0.1238)
No income reported			1.234***	0.767***	1.271***	0.775***
			(0.1148)	(0.0945)	(0.1146)	(0.0899)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE × Wave FE	No	No	No	No	Yes	Yes
Observations	102,947	102,947	102,609	102,609	102,609	101,875
Clusters (country-years)	102	102	102	102	102	101
Countries	30	30	30	30	30	30
Pseudo R^2	0.1696	0.2768	0.2218	0.3313	0.2300	0.3359

Notes Logit estimations with standard errors clustered at the country-year level. Analysis is restricted to the age group of the 18–60-year-old. “Employed” refers to doing full-time employment, part-time employment, or freelance work, with unemployed, housewives/housemen and early retired serving as comparison group. “Active” includes both employed and unemployed. “***”, “**” and “*” indicate statistical significance at the 1, 5 and 10 percent levels, respectively. Estimated with Stata 13

Table 13.8 Predicted employment probabilities for men and women

Economic glob. (log)	Men (%)	Women (%)	Info. glob. (log)	Men (%)	Women (%)
2	92.64	69.48	2	99.88	68.68
3	90.29	65.15	3	98.84	64.67
4	87.33	60.56	4	90.38	60.45
5	83.68	55.78	5	55.31	56.86

Notes Measured at respondents' mean age of 38 years. Based on column (1) of Table 13.2

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Biography

Justina A. V. Fischer did her Ph.D. in Economics at the University of St. Gallen (CH) and the European University Institute (I), followed by research stays at the LSE (UK) and the University of Stanford (USA). With several Marie Curie research grants, she was a visiting fellow at the Stockholm School of Economics (SE), the University of Rome (I), and the University of Bern (CH). She is currently a visiting fellow at the University of Mannheim (D) and serves as an associate professor at the Technical University of Chemnitz (D).

Part IV
Regional Policy

Chapter 14
Structural Funds and Regional Convergence: Some Sectoral Estimates for Italy*

Gianluigi Coppola and Sergio Destefanis

Abstract In this chapter, we assess the European Structural Funds' effects on the economies of the 20 Italian administrative regions for the period 1989–2006. The principal novelties of this chapter are that the empirical analysis separately considers the effects on four sectors (agriculture, energy and manufacturing, construction, and services), and we employ a non-parametric FDH-VP to calculate Malmquist productivity indexes. This allows us to distinguish the Funds' effects on factor accumulation from those on total productivity changes. Our evidence implies that the Funds had a weak, but significant, impact on total factor productivity change but virtually no effect on capital accumulation or employment. Different types of Structural Funds are found to have widely different influences, with the European Social Fund, arguably, having the strongest impact.

Keywords European Structural Funds • Total factor productivity • Non-parametric frontiers • Malmquist index

JEL Classification C43, D24

14.1 Introduction

In this chapter, we assess the European Structural Funds' effects on the economies of the 20 Italian administrative regions. We focus on the impact these Funds have on productivity and factor accumulation. This is a topic of considerable policy interest. In recent years, there has been a lively policy debate (not only in Italy

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but also in the rest of Europe)[1] on the role of public investment programmes. The Funds are, especially since the introduction of *Agenda 2000*, the European Community's primary instrument to sustain development in areas facing economic problems. Moreover, since the inception of the EMU, interest in studies concerning the economic performance of European regions has increased considerably. In this respect, the Italian case appears particularly interesting. Italy is characterised by marked regional heterogeneity. As is well known, the Mezzogiorno[2] regions of Italy have consistently lagged behind the rest of the country in terms of per capita income and economic performance (Allen and Stevenson 1974; Putnam 1993; Paci and Saba 1998).

The principal main element of novelty of the present work vis-à-vis the existing literature (Boldrin and Canova 2001; Garcìa-Solanes and Maria-Dolores 2002a, b; Aiello and Pupo 2007) is that our empirical analysis separately considers four sectors (agriculture, energy and manufacturing, construction, services). Furthermore, a non-parametric approach (FDH-VP, see Kerstens and Vanden Eeckaut, 1999; Destefanis and Storti 2002; Destefanis 2003) is employed to measure technical efficiency: By relying on these efficiency measures, Malmquist productivity indexes are calculated for three periods broadly corresponding to the programming periods of the Structural Funds (1989–1993, 1994–1999, and 2000–2006).[3] The indexes are computed separately for the 20 Italian administrative regions and the four sectors mentioned above. Then, standard regression techniques are adopted to establish whether the Funds have influenced factor accumulation and productivity changes. In this phase of our analysis, we rely (for the first time in the literature, to the best of our knowledge) on Structural Funds data from the Spesa Statale Regionalizzata (Ministero dell'Economia e delle Finanze, various years).

The remainder of the chapter is organised as follows. Section 14.2 presents the institutional set-up of the Funds, describing the EU Objectives, different types of Funds, and their evolution over the period 1989–2006, with a particular emphasis on Italy. Section 14.3 provides a survey of the extant empirical literature on the argument. Section 14.4 illustrates the empirical procedures and data, while the results of the empirical analysis are presented and commented on in Sect. 14.5. Section 14.6 concludes and presents implications for future research.

[1] See, for instance, Ministero dell'Economia (2001), Boldrin and Canova (2001), and the references therein. A classic reference is Biehl (1986). The main topics of the debate are effectively summarised in Tondl (2004).

[2] These regions are Abruzzo, Molise, Campania, Puglia, Basilicata, Calabria, Sicilia, and Sardegna.

[3] The limited availability of regional accounting data prevents the inclusion of more recent data in this study.

14.2 European Structural Funds: The Institutional Set-Up

It does not seem feasible to advance toward a closer integration of the EU countries without fostering ever-greater economic and social cohesion among them. Yet, even at present, very deep economic and social gaps persist (both across countries and regions) that undermine the unity and cohesion of the Union. Even in the former 15-country Union, the GDP per capita of the wealthiest areas (Hamburg, Paris) was ten to twelve times higher than that of the poorest regions of Greece or Portugal. In the face of these gaps, the creation of a monetary and economic union requires ever-greater efforts towards convergence, lest the weakest areas be permanently marginalised. Indeed, the monetary union leaves little leeway for country-level monetary (exchange-rate adjustments are no longer possible) or fiscal policy. The importance of economic and social cohesion is only made greater by the forthcoming enlargement of the EU to ten new countries from Central, Eastern, and Southern Europe; hence, the necessity of assessing the expediency and effectiveness of the development policies enacted through the Structural Funds.

As is well known, a variety of different financial instruments are gathered under the label of Structural Funds:

1. The European Regional Development Fund (ERDF) was created in 1975 with the aim of reducing regional imbalances in the EU. It targets less-developed regions and primarily finances projects involving investments in physical capital (private and public), support for small and medium firms, and R&D.
2. The European Social Fund (ESF) was created in 1986 with the aim of promoting training and the educational attainment among the labour force, as well as other forms of active labour market policies.
3. The European Agricultural Guidance and Guarantee Fund (EAGGF) dates back to 1962 and is a component of the Common Agricultural Policy. It aims to accelerate the adjustment of agricultural structures and contribute to the development of rural areas.[4]
4. The Financial Instrument for Fisheries Guidance (FIFG) was created in 1994 and replaced a number of smaller programmes concerning the fishing industry.

In the remainder of this chapter, we will not address the impact of the FIFG, given its highly specific nature. Moreover, we will not consider another important instrument of the EU's development policy: the Cohesion Fund. This fund, created in 1993 after the Maastricht Treaty, supports particular projects of member states (not regions) with GDP per capita levels below 90 % of the EU mean. As Italy does not satisfy this criterion, it is not a beneficiary of the Cohesion Fund, which consequently is not relevant to this chapter.

[4]On 1 January 2007, the EAGGF was replaced by the European Agricultural Guarantee Fund (EAGF) and the European Agricultural Fund for Rural Development (EAFRD). We will not address the EAGF or the EAFRD in this study.

The implementation of Agenda 2000 in 1999 corresponds to the fourth reform of the Funds system. The first reform of the Structural Funds occurred in 1984. However, the real turning point in the Funds' governance came in 1988 (Viesti and Prota 2007), after Spain and Portugal joined the EU in 1986. Indeed, in the second half of the 1980s, first with the White Paper (1985), and then with the Single European act, the EU was transformed from a free trade area into a single market. In 1986, Chapter V, titled "social cohesion", was added to the Treaty of Rome to emphasise the importance of the EU's cohesion policy. Under this new arrangement, which would lead to the EMU, social and economic cohesion policy sought to address the regional disparities linked to the centre–periphery dichotomy characterising the European economy (Krugman 1991a, b). These changes in the mission of EU cohesion policy led to a reform in 1988 with the following elements:

1. The reform of the EU's institutional balance, with an agreement on expenditure growth until 1992 and the introduction of budget revenue arrangements proportional to the GDPs of member states.
2. Increased EU resources for the cohesion policy. The annual payments increased from approximately ECU 6.4 billion in 1988 to ECU 20.5 billion in 1993, and their relative share jumped from 16 to nearly 31 % of the EU budget (European Union Regional Policy 2006).
3. The reform of the Common Agricultural policy.

Furthermore, four new guidelines concerning the Funds were introduced:

1. Functional and geographic concentration
2. Planning (multi-annual programme planning)
3. Partnership among the EU, the member states, and their regions, which implied a closer dialogue between the European Commission and the regional and national administrations, through the presentation of development plans
4. Additionally, the EU funds did not substitute for national funds but were added to them.

Specifically, the concentration principle implied a limited number of objectives for cohesion policy. To achieve them, the Funds are primarily distributed to a restricted subset of regions. The five basic Objectives dictating how the various Funds must interact were originally defined as follows:

Objective 1 Economic and structural adaptation of less-developed regions; this includes all regions with GDP per capita levels below 75 % of the EU average over the last 3 years. In Italy, these regions include Abruzzo (until 1996), Molise (until 2006), Campania, Puglia, Basilicata, Calabria, Sicilia, and Sardegna.

Objective 2 Economic recovery of regions affected by industrial crisis (as defined by three eligibility criteria). In Italy, this objective applies to provinces (NUTS3 areas) in Abruzzo, Emilia Romagna, Friuli Venezia Giulia, Lazio, Liguria, Lombardia, Marche, Piemonte, Toscana, Trentino Alto Adige, Umbria, and Valle d'Aosta e Veneto.

Objective 3 Combating long-term unemployment. The territorial target of this Objective (and the following one) covers the entire EU.

Objective 4 Facilitating the adaptation of workers to industrial changes and changes in production systems.

Objective 5 Accelerating the adjustment of industrial structures. Objective 5a covers the entire EU, while the territorial target of Objective 5b (focusing on marginalised areas) comprises areas with high levels of agricultural employment, low levels of agricultural income, low population density, and/or a significant depopulation trend.

The changes implemented under the third Reform of the Fund system, which occurred in 1993, were much less radical than those in 1988. The most important novelties are:

1. Financial resources were doubled.
2. Changes in the Objectives with the aim of better addressing the problem of unemployment:
   - The new Objective 3 includes the functions of the former Objectives 3 and 4 with the goal of facilitating the inclusion of individuals in the labour market otherwise at risk of being marginalised.
   - The new Objective 4 must guarantee (through the ESF) the adaptation of workers to industrial change and the evolution of production systems.
   - Objective 5b also includes aid to modernise and restructure the fishing industry, through the institution of the FIFG.

The fourth Reform (implemented through the so-called *Agenda 2000*) follows three main axes:

1. Financial resources for the 2000–2006 period are maintained at the levels of the 1994–1999 period, equal to the 0.46 % of the EU's GDP.
2. Attempts are made to improve the effectiveness of the Funds through:
   - A greater concentration of aid (There are now three Objectives instead of six)
   - A clearer allocation of responsibilities among the Commission and member states
   - Strengthen the procedures related to control, monitoring, and evaluation.
3. The partial extension of the Fund system to prospective member states.

The main features of the Funds' distribution across periods and regions can be understood by observing the three figures below. The order in which the regions are presented is detailed in the Appendix. Roughly, we proceed southwards as we move from left to right (Figs. 14.1, 14.2, and 14.3).

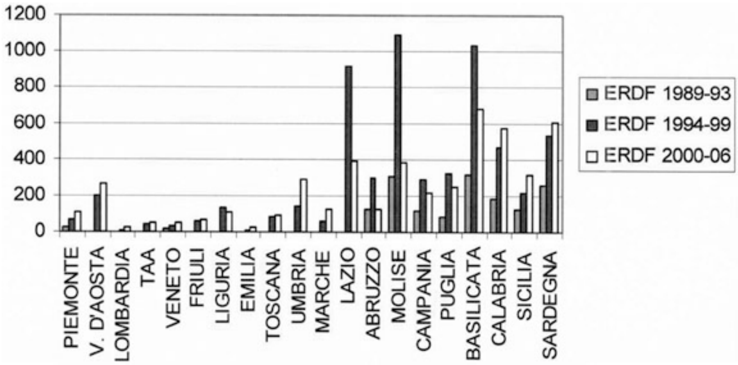

Fig. 14.1 The ERDF, disbursed funds, by Italian region in Euros per inhabitant (1995 prices). Periods 1989–1993, 1994–1999, and 2000–2006. *Source*: our elaborations based on Istat and MEF (*Spesa Statale Regionalizzata*) data

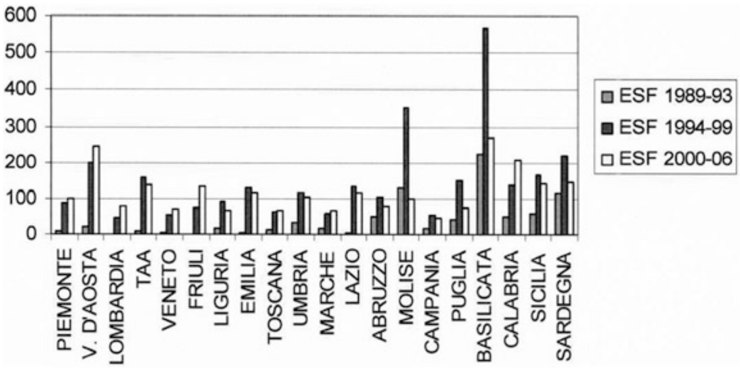

Fig. 14.2 The ESF, disbursed funds, by Italian region in Euros per inhabitant (1995 prices). Periods 1989–1993, 1994–1999, and 2000–2006. *Source*: our elaborations based on Istat and MEF (*Spesa Statale Regionalizzata*) data

Funds per inhabitant are much higher in the Mezzogiorno regions, especially with respect to the ERDF. However, note that there is considerable variation even among the Mezzogiorno regions. Particularly high values are obtained for Molise and Basilicata.

It is also instructive to consider the Funds as a percentage of regional GDP. As Table 14.1 indicates, the Funds typically represent a minuscule share of regional GDP, again attaining higher values in the Mezzogiorno and smaller regions.

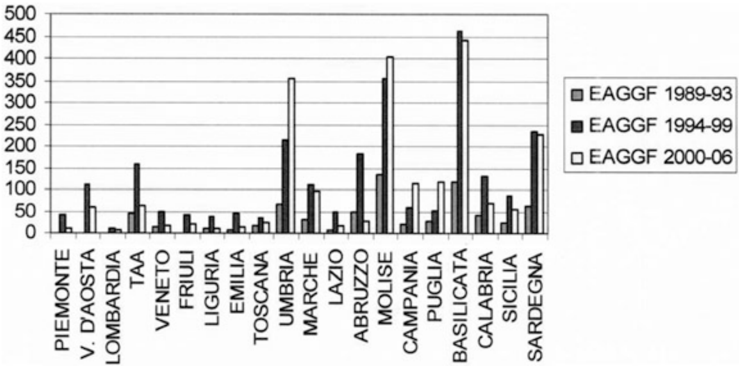

Fig. 14.3 The EAGGF, disbursed funds, by Italian region in Euros per inhabitant (1995 prices). Periods 1989–1993, 1994–1999, and 2000–2006. *Source*: our elaborations based on Istat and MEF (*Spesa Statale Regionalizzata*) data

Table 14.1 The European structural funds, disbursements by Italian region, as a share of regional GDP. Periods 1989–1993, 1994–1999, 2000–2006

	ERDF 1989–1993 (%)	ERDF 1994–1999 (%)	ERDF 2000–2006 (%)
PIEMONTE	0.14	0.21	0.29
V. D'AOSTA	0.00	0.38	0.30
LOMBARDIA	0.00	0.02	0.02
TRENTINO AA	0.00	0.09	0.05
VENETO	0.09	0.15	0.08
FRIULI VG	0.00	0.15	0.10
LIGURIA	0.00	0.33	0.24
EMILIA R.	0.00	0.02	0.04
TOSCANA	0.00	0.31	0.08
UMBRIA	0.00	0.54	0.97
MARCHE	0.00	0.27	0.33
LAZIO	0.00	0.05	0.13
ABRUZZO	0.94	0.53	0.29
MOLISE	2.63	2.95	1.19
CAMPANIA	1.19	0.70	0.94
PUGLIA	0.79	0.86	0.74
BASILICATA	3.27	3.16	2.09
CALABRIA	1.98	1.25	1.62
SICILIA	1.20	0.45	1.12
SARDEGNA	2.23	1.31	1.85

(continued)

Table 14.1 (continued)

	ESF 1989–1993	ESF 1994–1999	ESF 2000–2006
PIEMONTE	0.06	0.19	0.16
V. D'AOSTA	0.09	0.37	0.44
LOMBARDIA	0.00	0.05	0.15
TRENTINO AA	0.04	0.27	0.25
VENETO	0.02	0.11	0.14
FRIULI VG	0.00	0.17	0.27
LIGURIA	0.10	0.19	0.13
EMILIA R.	0.02	0.21	0.19
TOSCANA	0.08	0.13	0.12
UMBRIA	0.22	0.24	0.28
MARCHE	0.12	0.08	0.14
LAZIO	0.03	0.09	0.05
ABRUZZO	0.39	0.25	0.19
MOLISE	1.10	1.08	0.24
CAMPANIA	0.15	0.10	0.23
PUGLIA	0.40	0.45	0.13
BASILICATA	2.30	2.12	1.09
CALABRIA	0.53	0.43	0.21
SICILIA	0.57	0.51	0.40
SARDEGNA	0.98	0.64	0.46
	EAGGF 1989–1993	EAGGF 1994–1999	EAGGF 2000–2006
PIEMONTE	0.01	0.06	0.01
V. D'AOSTA	0.00	0.06	0.03
LOMBARDIA	0.00	0.01	0.01
TRENTINO AA	0.23	0.20	0.08
VENETO	0.07	0.05	0.02
FRIULI VG	0.00	0.06	0.02
LIGURIA	0.06	0.04	0.01
EMILIA R.	0.04	0.04	0.01
TOSCANA	0.10	0.07	0.02
UMBRIA	0.44	0.52	0.97
MARCHE	0.20	0.20	0.24
LAZIO	0.05	0.03	0.02
ABRUZZO	0.36	0.45	0.04
MOLISE	1.13	1.82	0.60
CAMPANIA	0.21	0.23	0.21
PUGLIA	0.28	0.21	0.47
BASILICATA	1.23	1.38	1.69
CALABRIA	0.44	0.36	1.29
SICILIA	0.24	0.31	0.40
SARDEGNA	0.54	0.81	0.75

Source: our elaborations on Istat and MEF (*Spesa Statale Regionalizzata*) data

14.3 A Brief Overview of the Empirical Literature

The literature on the impact and effectiveness of European regional policy is substantial. We will provide a brief account of it. Further information can be found in a recent survey by Prota and Viesti (2013). First, the empirical results presented in this literature are discordant. They are highly dependent on the data set used, the period considered, and the methods and models applied. Nevertheless, as noted by Prota and Viesti (2013), it is possible to distinguish two different methodological approaches: macroeconomic simulation models and econometric models. The former, such as Hermin or Quest, generally find that regional policy has a positive impact, in both the short and long run, on GDP and employment. The size of the impact observed typically varies across countries. However, the application of econometric models yields different and occasionally opposite results.[5] Based on the results, these analyses can be classified into three groups. The first includes papers that find a negative, or nearly insignificant, impact of the Funds on the convergence process. The second group, on the contrary, finds that the impact is positive. Papers in the third group argue that the effects of the Funds crucially depend on the initial conditions of the regions where they are allocated.

The first group of papers is well represented by Boldrin and Canova (2001). They attempt to identify three types of evidence. First, they wish to ascertain whether regional differences in income per capita, labour productivity, and total factor productivity are increasing or decreasing over time (they consider the period from 1980 to 1996). According to their evidence, regional disparities are not substantially affected in either sense.[6] Then, Boldrin and Canova proceed to identify the main factors affecting the evolution of these disparities. Regional differences in income per capita can be captured by a combination of three factors: total factor productivity, the employment rate, and agriculture as a share of GDP. In their view, agglomeration effects (often invoked by the European Commission as a rationale for interregional transfers) do not help to explain the differences in growth rates.

Boldrin and Canova finally consider the direct impact of Structural Funds on regional differences in productivity. Primarily relying on non-parametric tests, they compare the changes in the empirical distribution of regional productivities over time and find that recipient and non-recipient regions behave much in the same manner. Their conclusion is that regional policies can generally be rationalised in terms of redistributive practices, motivated by the nature of the political equilibria on which the EU is built.

Boldrin and Canova's paper is well constructed and thought provoking. It certainly provides evidence to the effect that the Structural Funds do not generate any *large* effects. In some respects, however, their analysis is not entirely

[5] Marzinotto (2012) shares the view that there is a sharp division between the results of macroeconomic simulations and other types of empirical analysis.

[6] However, Italy is a partial exception to this: its southern regions lagged somewhat behind other regions in the period under study.

convincing. In particular, the analysis of the elements that determine regional differences in labour productivity and income per capita would benefit from further evidence: for instance, no measurement of returns to scale is attempted. Further, the assessment of the direct impact of the Structural Funds excessively relies on an empirical instrument (the assessment of changes in the empirical distributions of productivities) that cannot simultaneously capture the effects of different (and possibly contrasting) factors.

An empirical approach that would allow us assess the impact of Structural Funds on productivity in conjunction with the eventual effects of other factors is to estimate Barro-type regressions that explicitly assess whether β-convergence is a function of the Structural Funds. This approach is employed by Garcìa-Solanes and Maria-Dolores (2002a, b), which belong to the second group of papers. Garcìa-Solanes and Maria-Dolores (2002a) focus on EU member states and regions. In the first case, the data include the two programming periods, 1989–1993 and 1994–1999, while in the second case, the analysis stops in 1996 for reasons of data availability. In both cases, the authors implement a dynamic β-convergence test in an equation with fixed effects that allows each country or region to converge to an idiosyncratic steady state. Crucially, their Barro-type regressions include the amounts of Funds distributed to countries or regions during the two programming periods. They account for an aggregate measure of Structural Funds per inhabitant, as well as measures of ERDF, ESF, and EAGGF Funds per inhabitant. Their results indicate that the inclusion of Funds in the regressions increases the estimated speed of convergence and has a significant impact on the steady-state growth rate implied by the equation. These effects are stronger in the country (as opposed to the region) regressions.

In a refinement of their analysis, Garcìa-Solanes and Maria-Dolores (2002b) account for the fact that Funds are not randomly distributed across regions, which implies the possible existence of selection bias in the above estimates. They do so by nesting the β-convergence test within the switching model approach first proposed in Quandt (1972) and Goldfeld and Quandt (1972). They find that, even allowing for this possible bias, the Funds have a positive impact on growth.

Aiello and Pupo (2007) focus on the territorial effects of EU spending from 1996 to 2007. An important feature of their work, vis-à-vis previous studies, is that they use data on *actually spent*, rather than *accredited funds*. Their empirical analysis is based on panel estimates of an expanded neoclassical growth model in which Structural Funds are included among the variables that explain the convergence across Italian regions. Using various dynamic panel estimators, Aiello and Pupo find that the Funds, although having a stronger impact in the South than in the Centre-North, have not significantly contributed to regional convergence in Italy. For this reason, their work may be included in the third group of papers.

Clearly, macroeconomic simulations have a richer structure than other types of econometric analyses. Yet they also rely on many more (often untested) hypotheses concerning model specification (variables included, certain key parameters, dynamic structure, functional form, etc.). We do not wish to take sides in the simulation vs. estimation debate, which would go beyond the scope of our chapter.

We aim to provide room for a more articulated analysis that could be useful for future empirical works of any type.

In a sense, we employ the Garcìa-Solanes and Maria-Dolores studies as a benchmark. There are, however, some important differences. First, we use sectoral data to better understand the way in which the Funds affect different industries. Second, in an attempt to provide useful policy indications, we separately analyse the effects of Funds on factor accumulation and variations in total factor productivity. Furthermore, we divide the latter into technical change, variations in pure technical efficiency, and variations in scale efficiency by calculating Malmquist productivity indexes (Färe et al. 1994, 1997; Ray and Desli 1997; Balk 2001). The channels through which the Funds can affect variations in total factor productivity are then also assessed separately.

14.4 The Empirical Framework

In principle, Structural Funds have a twofold economic impact. First, these transfers increase income in the benefited regions, generating a Keynesian (or demand) effect on output and employment. This impact is likely to be short lived. However, the transfers may also increase the productive capacity of these regions, which is their primary aim (European Commission 2000; p. 155). The latter impact can be gauged by assessing the relationship between the Funds and factor accumulation, as well as variations in total factor productivity. In this section, we consider how the latter can be measured. A brief presentation of the data set follows.

14.4.1 The Malmquist Index

It is well known that calculating Malmquist productivity indexes values across two sub-periods yields estimates of the variations in total factor productivity and their components: technical change, variations in pure technical efficiency, and variations in scale efficiency. Yet, when the production technology exhibits non-constant-returns to scale, there is no consensus in the literature on how to account for scale effects. Here, we follow the approach suggested in Balk (2001). The variations in total factor productivity are measured against a constant-returns to scale benchmark, which is the only way to obtain a productivity index that respects certain basic properties. Then, technical change is evaluated as the shift in the true production frontier (eventually exhibiting non-constant-returns to scale), while the variation in technical efficiency is decomposed into the variation in pure technical efficiency (with respect to the true frontier) and the variation in scale efficiency. The latter is measured while holding technology constant, that is, evaluating variations in scale efficiency obtained for different input values on a given production frontier (on this, see Balk 2001). Formally, to simplify our analysis, let us assume a single-output production process.[7] Denote then by $D^{s}(x_t, y_t)$, the following output-oriented distance function:

$$D^{s}\left(x_t, y_t\right) = \inf\left\{\theta : \left(x_t, y_t/\theta\right) \in T_{s}\right\}. \tag{14.1}$$

Similarly, define

$$\Delta^{s}\left(x_t, y_t\right) = \inf\left\{\theta : \left(x_t,\ y_t/\theta\right) \in \Theta_{s}^{crs}\right\} \tag{14.2}$$

where Θ_{s}^{crs} is a benchmark constant-returns to scale technology defined along the ray corresponding to the optimal production scale. The Malmquist index measuring variations in total factor productivity on the interval $\Delta t = [t, t+1]$ allows the following decomposition:

$$M_{t,\,t+1} = \text{DTE} \times \text{TC} \times \text{DSE} \tag{14.3}$$

where

$$\text{DTE} = \frac{D^{t+1}\left(x_{t+1}, y_{t+1}\right)}{D^{t}\left(x^{t}, y_t\right)} \tag{14.4}$$

is the (relative) variation in pure technical efficiency and measures the extent to which any observation approaches the frontier from one period to the next.

$$\text{TC} = \left[\frac{D^{t}\left(x_{t+1}, y_{t+1}\right)}{D^{t+1}\left(x_{t+1}, y_{t+1}\right)} \times \frac{D^{t}\left(x_t, y_t\right)}{D^{t+1}\left(x_t, y_t\right)}\right]^{1/2} \tag{14.5}$$

measures technological change, that is, the shift in the frontier, measured across two periods as the geometric mean of the frontier shifts occurring at either data point. Finally,

$$\text{DSE} = \left[\frac{\Delta^{t}\left(x_{t+1}, y_{t+1}\right)/D^{t}\left(x_{t+1}, y_{t+1}\right)}{\Delta^{t}\left(x_t, y_t\right)/D^{t}\left(x_t, y_t\right)} \times \frac{\Delta^{t+1}\left(x_{t+1}, y_{t+1}\right)/D^{t+1}\left(x_{t+1}, y_{t+1}\right)}{\Delta^{t+1}\left(x_t, y_t\right)/D^{t+1}\left(x_t, y_t\right)}\right]^{1/2} \tag{14.6}$$

is the (relative) variation in scale efficiency. Expression (14.6) can perhaps be best appraised using the graphical example provided in Fig. 14.4. As is standard in the literature, we consider a one-input and one-output technology.

$F(t)$ denotes the true frontier at time t and $C(t)$ the virtual CRS frontier (providing the optimal scale for any observation at time t). $F(t+1)$ and $C(t+1)$ are the same concepts at time $t+1$. Considering observation 1 at t and $t+1$, the relative

[7]The single-output assumption does not imply any loss of generality, as an analogous decomposition holds for the multi-output case (see Balk 2001).

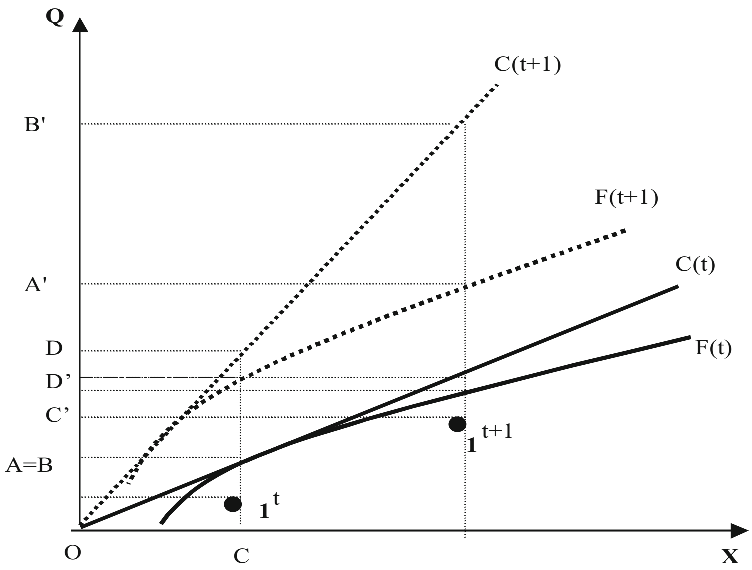

Fig. 14.4 Measuring the variations in scale efficiency

variations in scale efficiency as measured by Balk (2001) are given by the following formula:

$$\mathrm{DSE} = \left(\frac{\frac{\mathrm{OC}'}{\mathrm{OD}'}}{\frac{\mathrm{OA}}{\mathrm{OB}}}\right)^{1/2} \times \left(\frac{\frac{\mathrm{OA}'}{\mathrm{OB}'}}{\frac{\mathrm{OC}}{\mathrm{OD}}}\right)^{1/2} \tag{14.7}$$

Now, if one assumes that labour and the stock of physical capital are the only inputs, it is possible to write the following expression (a similar approach was employed in Kumar and Russell 2002):

$$\mathrm{DOUTPN} = M_{t,\,t+1} \times \mathrm{DKAPN} \times \mathrm{RES} \tag{14.8}$$

The relative variation in output per labour unit (DOUTPN) is decomposed into the relative variation in TFP (as measured by $M_{t,\,t+1}$), a component linked to the relative variation in the stock of capital per labour unit (DKAPN), and a residual component (RES). Thus, it is possible to write:

$$\mathrm{DOUTPN} = \mathrm{DTE} \times \mathrm{TC} \times \mathrm{DSE} \times \mathrm{DKAPN} \times \mathrm{RES} \tag{14.9}$$

where DTE, TC, and DSE are measured in the manner suggested above. Expression (14.9) allows one to jointly consider the impact on the relative variations in output per labour unit of (the relative variations in) the stock of capital per labour unit and the relative variations in the components of TFP. The Structural Funds' impact on each of these elements can then be assessed through regression techniques. Obviously, we still need to select appropriate measures for the DTE, TC, and DSE components of the Malmquist index. Below, we consider some developments in the quantitative analysis of production for this purpose.

14.4.2 The FDH-VP Approach

The so-called non-parametric approach to the quantitative analysis of production provides empirical counterparts of (14.1) and (14.2) without supposing the existence of a functional relationship between inputs and outputs. Beginning with the seminal contribution of Farrell (1957), this approach is employed to determine the frontier of a production set (which only satisfies a limited number of restrictive assumptions that are specified a priori). The frontier is supported by some of the observed producers, which are defined as efficient.

Non-parametric methods are divided between those that impose the hypothesis of convexity on the production set (typically gathered under the label of Data Envelopment Analysis, or DEA) and those that do not require this assumption (the Free Disposal Hull—FDH—approach proposed in Deprins et al. 1984 and Tulkens 1993). In the latter case, the only property imposed on the production set is strong input and output disposability, while DEA requires the additional hypothesis of convexity. More formally, in FDH, for a given set of producers Yo, the reference set Y (Yo) is characterised, in terms of an observation i, by the following postulate:

$$\left(\mathbf{X}^{\mathrm{i}}, \mathbf{Y}^{\mathrm{i}}\right) \text{ observed, } \left(\mathbf{X}^{\mathrm{i}} + \mathbf{a}, \mathbf{Y}^{\mathrm{i}} - \mathbf{b}\right) \in Y\,(Y\mathrm{o})\,,\ \mathbf{a}, \mathbf{b} \geq 0 \tag{14.10}$$

where **a** and **b** are vectors of free disposal of inputs and outputs, respectively. In other words, due to the possibility of free input and output disposability, the reference set includes all the producers employing the same or greater levels of more inputs and producing the same level or less output relative to observation i.

Let us take as an example Fig. 14.5, where we consider a technology with one input (X) and one output (Y). The input–output pairs correspond to a cross section of producers examined at a given point in time. Beginning with observation B, we define every observation located to its right and/or below it (i.e. using more of the input and to produce the same level of output, producing less output with the same level of the input, or using more of the input and producing less output, such as F) as dominated by B.

In the FDH approach, this comparison is made for every observation, and the observations dominated by other producers are considered inefficient. Those units that are not dominated by any other observation are instead considered efficient producers, belonging to the frontier of the reference set.

Employing FDH allows us to abandon the hypothesis that the production set is convex, which is typical of DEA. This means that the frontier obtained through FDH is likely to more closely fit the data than that obtained through DEA, if the reference

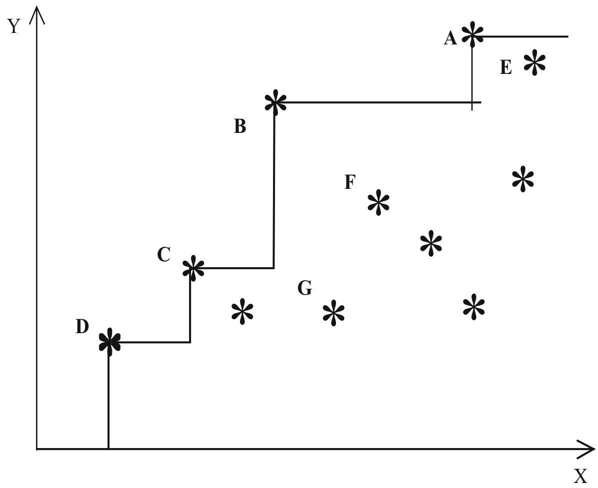

Fig. 14.5 The FDH technology

set is characterised (at least locally) by the existence of non-convexities.[8] Moreover, as the frontier of the reference set comprises units that actually exist (rather than by a convex hull), FDH will be less sensitive to the presence of outliers (or erroneously measured values) in the reference set than DEA. More precisely, the part of the frontier influenced by the presence of the outlier will be smaller under FDH than DEA. One problem with traditional FDH is that some observations may be efficient because they are located in a region of the production set where there are no other observations with which they can be compared (*efficiency by default*). This problem is particularly relevant when small data sets (such as ours) are used. To avoid this problem, we use a refinement of the FDH, the FDH-VP (variable-parameter FDH) proposed by Kerstens and Vanden-Eeckaut (1999). This approach imposes more structure on the production set: each observation is compared not only to any other observation but also to their smaller or larger proportional replicas. In this chapter, we employ an output-oriented[9] FDH-VP approach to calculate the *DTE*, *TC,* and *DSE* components of the Malmquist index of productivity.

[8]It has been observed (Mundlak et al. 1999; Mundlak 2000) that in cross-country (or cross-region) productivity comparisons, one must rely on empirical aggregate production frontiers obtained from unobservable micro frontiers. In this case, when the available technology includes more than one technique, modifying the environment faced by producers may lead to changes in techniques (as well as to changes in the output–input mix for a given technique), and the hypothesis of convexity may not be respected for the observable aggregate production frontiers.

[9]We do not claim any strong theoretical basis for this choice. However, if we adopt an input orientation, in a two- or three- input space, the commonly adopted Debreu–Farrell measure of efficiency may not measure technical efficiency (in the sense of Koopmans 1951) exhaustively. On this, see Lovell (1993).

14.4.3 The Data

To compute technical efficiency measures and, in turn, Malmquist productivity index values, we rely on a baseline production set with value added as the output and the number of labour units and stock of private capital as inputs. Regional data for these variables are considered for four industries: agriculture, energy and manufacturing, construction, and services. The latter cannot be divided into market and non-market services because the allocation of these services to different industries considerably changed with the new SEC95 national accounting (see, for instance, Collesi 2000).[10] Capital stock series were constructed following the procedure in Paci and Pusceddu (2000).

To examine the employment performance of Italian regions, it seems appropriate to focus on the employment rate (more precisely, the relationship between labour units and the resident population), both for the entire regional economy and for the four sectors under examination. This measure is less affected by the discouraged-worker effect than the unemployment rate, and it is easy to calculate both at the sectoral and the aggregate level. The resident population series was reconstructed using the procedures suggested in Golinelli and Monterastelli (1990).

The Structural Funds series were taken from the series *Spesa statale regionalizzata* of the Ministero dell'Economia e delle Finanze. The series were deflated using a regional GDP deflator and divided by the regional number of inhabitants. It must be stressed that these series relate to the amounts disbursed by the various regions, as taken from the *Spesa Statale Regionalizzata*. More precisely, these data are directly available from 1994 onwards. From 1989 to 1993, we relied on the Funds accredited to the various regions by the EU (source: *I flussi finanziari Italia/UE*—Ragioneria Generale dello Stato, Ministero dell'Economia e delle Finanze, various years) and corrected that amount using information on payment data from the EU. This marks a distinctive change with respect to the analysis in Coppola and Destefanis (2007), where we simply used the Funds *accredited* to the various regions by the EU. It is well known that, in certain instances, the regions were unable to disburse these amounts within the prescribed timeframe. In this sense, there is a potentially serious measurement error with the Structural Fund data we employed in the past. However, relying on the *Conti Pubblici Territoriali*, as in Aiello and Pupo (2007), would considerably restrict the sample (no such data are available before 1996).

[10]Consistent pre- and post-SEC95 series for value added and the number of labour units were generously provided by Roberto Basile of ISAE, Rome.

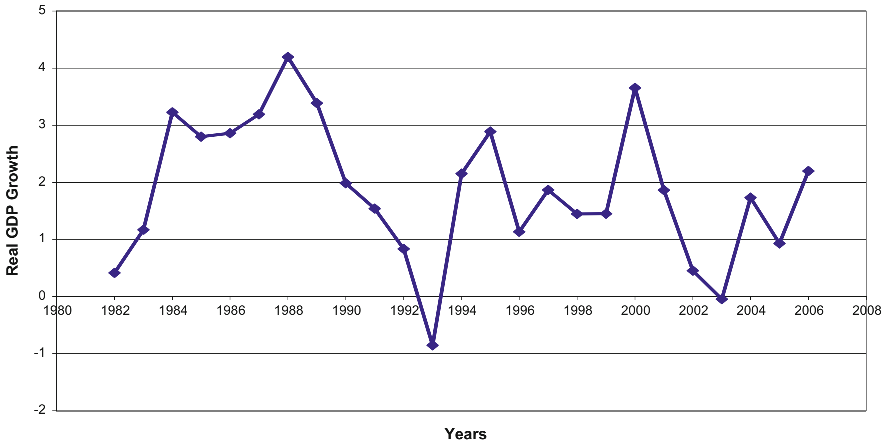

Fig. 14.6 The Italian cycle, real GDP growth, 1982–2006. *Source*: our elaborations based on ISTAT data

14.5 Structural Funds, Productivity, and Factor Accumulation Across the Italian Regions

Some contributions (Kittelsen 1999; Simar and Wilson 2000) highlight the possibility that non-parametric frontier methods may encounter small-sample problems for sample sizes close to or smaller than 100 observations. Accordingly, FDH-VP is applied not on single years but on four sub-samples that approximately correspond to cyclical phases of the Italian economy: 1982–1987, 1988–1993, 1994–1999, and 2000–2006. Some prima facie evidence concerning the correspondence between our sub-samples and the Italian cycles is presented in Fig. 14.6.

The basic assumption behind the procedure of applying FDH-VP to multi-year periods is that the state of technology should not change appreciably within any one of these sub-samples. The sub-sample means for the technical efficiency scores are then used to compute cross-period Malmquist indices, which turn out to be almost exactly contemporaneous with the Funds' programming periods (1989–1993, 1994–1999, and 2000–2006).

As explained in Kerstens and Vanden-Eeckaut (1999) and Destefanis (2003), FDH-VP can also be employed to produce a measure of the scale elasticity of the production frontier. This measure is used here to provide a quantitative assessment of the argument developed in Boldrin and Canova (2001) to the effect that the elements claimed to be the source of agglomeration effects and growing regional inequality (primarily, the existence of increasing returns) are not particularly important. Let us first turn to the results concerning the existence of increasing returns, which according to Boldrin and Canova (2001) are paramount among the elements claimed to be the source of growing regional disparities. Regional cross-period means for the scale elasticities computed through FDH-VP are reported in

Table 14.2 Regional measures for the elasticity of scale[a]

Regione	Agriculture	Energy and manufacturing	Construction	Services
Piemonte	0.84	1.03	0.92	1.01
Valle d'Aosta	1.20	1.10	1.07	1.00
Lombardia	0.81	0.99	0.90	1.00
Trentino A A	0.80	1.10	1.04	1.00
Veneto	0.80	1.00	0.91	1.01
Friuli V G	0.80	1.08	0.99	1.00
Liguria	1.03	1.05	0.93	1.01
Emilia Romagna	0.80	1.08	0.90	1.00
Toscana	0.80	1.05	0.93	1.01
Umbria	1.09	1.08	1.08	1.01
Marche	0.82	1.01	1.00	1.01
Lazio	0.80	1.03	0.90	1.00
Abruzzo	0.93	1.08	0.90	1.01
Molise	1.20	1.10	1.10	1.01
Campania	0.80	1.07	0.90	1.01
Puglia	0.80	1.04	0.90	1.00
Basilicata	0.89	1.10	1.06	1.00
Calabria	0.80	1.10	0.94	1.01
Sicilia	0.80	1.08	0.90	1.01
Sardegna	0.80	1.10	1.04	1.00
Media	**0.88**	**1.06**	**0.97**	**1.01**

[a]The elasticity of scale measures the percentage increase in output due to a unit percentage increase of all inputs. Values greater than (equal to, less than) one indicate the presence of increasing (constant, decreasing) returns to scale

The elasticity of scale was calculated using the formula suggested in Førsund (1996): the ratio between the natural logs of, respectively, input- and output-oriented technical efficiency scores

Table 14.2. They clearly indicate that energy and manufacturing is the only industry where increasing returns can be considered pervasive. Even there, however, they are not particularly strong. This evidence clearly supports Boldrin and Canova's claim that there are no strong divergence phenomena among European regions. Table 14.3 also makes it apparent that at least some tendency toward convergence is at work among the Italian regions. In this table, we compare the standard errors across the sub-samples under consideration for (the natural logs of) value added per labour unit and capital stock per labour unit, revealing the existence of some convergence between the economies of the Italian regions (apparently driven by processes taking place in services). This evidence, however, obviously does not clarify what type of convergence process is at work or the role that regional policies play in it.

Table 14.3 σ-Convergence: value added per labour unit

Period	Agriculture	Energy and manufacturing	Construction	Services	Total
1982–1987	0.39	0.12	0.12	0.11	0.15
1988–1993	0.43	0.13	0.19	0.11	0.14
1994–1999	0.42	0.12	0.16	0.09	0.11
2000–2006	0.39	0.12	0.21	0.08	0.10

Having obtained some measures for DTE, TC, and DSE (as well as for DOUPTN and DKAPN[11]), the Funds' impact on them is assessed using regression analysis. As is well known (see, for instance, Blundell and Costa Dias 2000), the crucial element in impact evaluation is the specification of the counterfactual hypothesis, that is, what would have been observed in the target areas in the absence of intervention. The fundamental problems in this respect are omitted variable bias (linked to the difficulty of measuring the effects of intervention separately from other factors) and selection bias (linked to the fact that Funds are not distributed randomly but on the basis of certain criteria, possibly impairing the comparison between target and non-target areas).

We address these problems by estimating the following fixed-effect regression:

$$\Delta x_{it} = \alpha_i + \alpha_1 \text{SOUTH} + \alpha_2 \text{PERIOD\_2} + \alpha_3 \text{PERIOD\_3} + \alpha_4 \text{PERIOD\_2} * \text{SOUTH} + \\ + \alpha_5 \text{PERIOD\_3} * \text{SOUTH} + \alpha_6 x_{it-1} + \alpha_{7j} \text{FUNDS}_{jit} + \alpha_8 z_{it} \tag{14.11}$$

where $i = 1, \ldots 20$, refers to the region, $t = 1, 2, 3$ to the period, and $t = 1, 2, 3$ to the Fund types (EAGGF, ERDF, ESF); Δx_{it} are the (percentage) variations in the variable of interest; PERIOD_2 is a dummy variable equal to 1 in the second period (1994–1999); PERIOD_3 is a dummy variable equal to 1 in the third period (2000–2006); SOUTH is a dummy variable equal to 0 for the non-Mezzogiorno regions and to 1 for the Mezzogiorno regions; PERIOD_n*SOUTH are interaction terms. Using these variables, we can account for systematic differences across time and regions and address, at least to some extent, both omitted variable and selection bias (in essence, Funds are awarded to the Mezzogiorno regions). Note that these variables can also account, at least to a first approximation, for the share of European Structural Funds that cannot be allocated to any single region.

The adoption of a fixed-effect approach, as suggested in Wooldridge (2002) for the purposes of policy evaluation, is also intended to address these problems. Through the x_{it-1} variable,[12] we allow for the dynamic structure inherent to the data. As catching-up phenomena are generally believed to appear in significant and

[11]Values for DOUPTN and DKAPN are obtained as percentage variations over the sub-sample means of the relevant variable.

[12]For technical progress, the lagged values of the state of technology were approximated using a Tornqvist index of total factor productivity.

negative coefficients of x_{it-1}, the omission of this variable could potentially lead to seriously biased estimates. Furthermore, this variable also allows us to mitigate the omitted variable and selection bias problems: the disbursement of funds is at least partly linked to past conditions. Including the (current) dependent variable in differences and its lagged counterpart in levels among the regressors does not imply a specification problem, provided that due account is taken of any non-stationarity in the means of this variable. In (14.11), this is achieved using the dummies PERIOD_2 and PERIOD_3.[13]

$FUNDS_{it}$ are the various funds (ERDF, ESF, EAGGF), included in the equation in natural logs (adding a unit constant to address cases in which funds were equal to zero[14]). Therefore, the α_{7j} coefficients can be interpreted as elasticities. We include all three Funds jointly in (14.11) in an attempt to avoid spurious results.

Finally, the z_{it} variable denotes the capital account expenditures (of national origin) accruing to a given region. Capital account expenditures are deemed to be of paramount importance to stimulate regional growth. It is also well known (Viesti and Prota 2007; Prota and Viesti 2013) that their amounts changed considerably during the period under analysis, generally decreasing. Therefore, omitting this variable (as we did in Coppola and Destefanis 2007) is a potential source of misspecification.

In Tables 14.4 and 14.5, we present the main evidence concerning the direct impact of Structural Funds on our variables of interest: the components of labour productivity change, the employment rate, and a measure of variations in total factor productivity obtained using a Tornqvist index.[15] The latter is included among the variables of interest to verify our evidence regarding the components of total factor productivity. If we find that these components are influenced by any of the Funds, we should be able to trace this influence back to the Tornqvist index (unless the components are associated with opposite signs).

The coefficients reported in Tables 14.4 and 14.5 are the α_{7j} values from (14.11), and the *t*-ratios are based on variance-covariance matrices corrected for unknown autocorrelation and heteroskedasticity (through the Newey-West procedure). We also report the estimated α_{8j} coefficients. In addition to the results for the four sectors, we also provide regression results relating to rates of change in regional GDPs and capital stocks per labour unit, as well as in regional GDPs per capita (denoted DOUTPC). The results can be summarised as follows.

First, it should be noted that z_{it}, the capital account expenditures, play a very limited role in our regressions. Subsequently, we present estimates of (14.11) with and *without* z_{it} (as the latter estimates may improve efficiency somewhat). Second,

[13]The appropriate unit root tests, the results of which are available upon request, failed to produce evidence against the hypothesis that the regression residuals are stationary.

[14]Regressions were also estimated by taking the ratio between the Fund values and their sample means, but this alternative specification did not substantially affect the results. In future work, we intend to consider the modelling of variables in greater detail, including zero values.

[15]This index is calculated using the value added, employment, and capital stock data, assuming constant-returns to scale and a labour share of output equal to 0.3.

Table 14.4 The impact of structural funds (specification with z_{it})[a]

	ERDF		ESF		EAGGF		z	
	Coeff.	T-ratio	Coeff.	T-ratio	Coeff.	T-ratio	Coeff.	T-ratio
Agriculture								
DOUTPN	**0.01**	0.44	**0.04**	0.73	**0.08**	1.86	**0.31**	2.49
DTE	**0.02**	1.09	**0.00**	0.09	**0.02**	0.53	**−0.02**	−0.32
TC	**−0.00**	−0.15	**0.03**	2.28	**0.01**	0.98	**0.03**	0.76
DSE	**−0.04**	−3.59	**0.07**	2.14	**−0.03**	−0.86	**0.04**	0.51
DKAPN	**−0.03**	−2.27	**−0.04**	−1.27	**0.01**	0.74	**0.00**	0.94
Dtfp	**0.02**	0.79	**0.05**	0.97	**0.07**	1.58	**0.30**	2.35
DER	**−0.01**	−0.50	**−0.02**	−0.51	**−0.04**	−1.70	**−0.01**	−0.11
Energy and manufacturing								
DOUTPN	**0.00**	0.44	**0.06**	3.92	**−0.01**	−1.13	**0.03**	1.08
DTE	**0.00**	0.76	**−0.01**	−0.51	**−0.00**	−0.16	**0.02**	0.70
TC	**0.00**	0.42	**0.01**	2.07	**0.00**	0.71	**−0.01**	−0.71
DSE	**0.00**	0.53	**0.01**	1.09	**−0.00**	−0.10	**−0.06**	−2.26
DKAPN	**−0.02**	−1.65	**0.01**	0.34	**−0.04**	−2.66	**−0.03**	−0.45
Dtfp	**0.01**	1.21	**0.05**	2.84	**0.01**	0.91	**0.05**	0.99
DER	**0.00**	0.00	**−0.02**	−0.15	**0.00**	0.09	**0.02**	0.42
Construction								
DOUTPN	**−0.03**	−1.70	**0.06**	1.58	**−0.05**	2.24	**−0.01**	−0.19
DTE	**−0.00**	−0.24	**−0.01**	−0.48	**−0.03**	−1.33	**−0.11**	−1.97
TC	**0.00**	0.35	**0.02**	2.22	**−0.02**	−2.26	**0.03**	1.50
DSE	**−0.01**	−0.66	**0.04**	1.77	**−0.05**	−1.49	**−0.10**	−1.82
DKAPN	**−0.02**	−1.36	**0.00**	0.15	**−0.01**	−0.77	**−0.11**	−1.79
Dtfp	**−0.02**	−1.34	**0.05**	1.42	**−0.04**	−1.87	**0.02**	0.23
DER	**0.01**	0.50	**−0.02**	−1.31	**0.02**	1.17	**0.00**	0.01
Services								
DOUTPN	**0.00**	0.15	**0.02**	2.11	**−0.01**	−1.45	**0.01**	0.30
DTE	**−0.01**	−2.75	**0.02**	5.59	**−0.01**	−0.73	**0.02**	0.40
TC	**0.01**	1.62	**0.00**	0.07	**0.01**	2.03	**−0.01**	−1.41
DSE	**−0.00**	−0.10	**−0.01**	−1.53	**0.00**	0.25	**0.01**	0.36
DKAPN	**0.02**	2.36	**−0.02**	−1.32	**0.00**	0.16	**0.07**	1.46
Dtfp	**−0.01**	−1.38	**0.04**	3.62	**−0.01**	−1.37	**−0.02**	−0.58
DER	**0.00**	0.10	**−0.00**	−0.68	**−0.00**	−0.38	**−0.01**	−0.60
Total								
DOUTPN	**−0.00**	−0.47	**0.03**	3.60	**−0.01**	−1.26	**0.01**	0.50
DKAPN	**0.02**	1.97	**−0.02**	−1.26	**−0.00**	−0.00	**0.04**	1.15
Dtfp	**−0.01**	−1.38	**0.04**	3.62	**−0.01**	−1.37	**−0.02**	−0.58
DER	**0.00**	0.03	**−0.01**	−1.79	**−0.00**	−0.72	**−0.01**	−0.89
DOUTPC	**−0.00**	−0.15	**0.02**	3.33	**−0.01**	−1.90	**0.00**	0.13

[a]This impact, to be interpreted as the elasticity of the dependent variable vis-à-vis a given Fund, is measured by coefficients α_{7j} in (14.11). To ease reading of the table, these coefficients are in bold characters (while their t-ratios are in normal characters).

Table 14.5 The impact of structural funds (specification without z_{it})

	ERDF		ESF		EAGGF	
	Coeff.	*T*-ratio	Coeff.	*T*-ratio	Coeff.	*T*-ratio
Agriculture						
DOUTPN	**0.02**	0.51	**0.00**	0.07	**0.11**	2.06
DTE	**0.02**	1.10	**0.01**	0.18	**0.01**	0.46
TC	**−0.00**	−0.10	**0.03**	2.37	**0.01**	1.14
DSE	**−0.04**	−3.49	**0.06**	2.15	**−0.03**	−0.78
DKAPN	**−0.03**	−2.28	**−0.05**	−1.38	**0.02**	0.76
Dtfp	**0.03**	0.75	**0.02**	0.30	**0.10**	1.77
DER	**−0.01**	−0.52	**−0.02**	−0.55	**−0.04**	−1.66
Energy and manufacturing						
DOUTPN	**0.00**	0.53	**0.06**	3.90	**−0.01**	−0.82
DTE	**0.01**	0.87	**−0.01**	−0.90	**0.00**	0.04
TC	**0.00**	0.36	**0.01**	2.02	**0.00**	0.56
DSE	**0.00**	0.57	**0.02**	2.47	**−0.01**	−0.89
DKAPN	**−0.02**	−1.60	**0.01**	0.53	**−0.05**	−2.86
Dtfp	**0.01**	1.51	**0.04**	2.67	**0.02**	1.18
DER	**0.00**	0.02	**−0.02**	−1.37	**0.00**	0.21
Construction						
DOUTPN	**−0.03**	−1.72	**0.06**	1.63	**−0.05**	2.17
DTE	**−0.01**	−0.41	**−0.00**	−0.01	**−0.04**	−1.79
TC	**0.00**	0.46	**0.02**	2.14	**−0.02**	−1.94
DSE	**−0.01**	−0.64	**0.06**	1.99	**−0.06**	−1.61
DKAPN	**−0.02**	−1.27	**0.02**	0.70	**−0.03**	−1.34
Dtfp	**−0.02**	−1.35	**0.05**	1.37	**−0.04**	−1.74
DER	**0.01**	0.50	**−0.02**	−1.35	**0.02**	1.18
Services						
DOUTPN	**0.00**	0.18	**0.02**	2.13	**−0.01**	−1.39
DTE	**−0.01**	−2.54	**0.02**	5.16	**−0.01**	−0.63
TC	**0.01**	1.56	**0.00**	0.44	**0.01**	1.73
DSE	**−0.00**	−0.08	**−0.01**	−1.86	**0.00**	0.39
DKAPN	**0.02**	2.04	**−0.03**	−1.89	**0.01**	0.56
Dtfp	**−0.01**	−1.11	**0.03**	2.84	**−0.02**	−1.86
DER	**0.00**	0.08	**−0.00**	−0.49	**−0.00**	−0.54
Total						
DOUTPN	**−0.00**	−0.45	**0.03**	3.66	**−0.01**	−1.72
DKAPN	**0.02**	1.79	**−0.03**	−1.96	**0.00**	0.42
Dtfp	**−0.01**	−1.38	**0.04**	4.06	**−0.01**	−1.68
DER	**−0.00**	−0.00	**−0.01**	−1.70	**−0.00**	−0.91
DOUTPC	**−0.00**	−0.15	**0.02**	3.43	**−0.01**	−2.27

it should be noted that, reassuringly, we observe some consistency between the Tornqvist index and changes in total productivity change, as computed from the Malmquist index.

Overall, our evidence implies that the Funds had a weak, but significant, impact on total factor productivity change but no positive effect on capital accumulation or employment. The power of our estimates, however, is relatively low and hence is likely to be affected by the relatively small size of our sample. Technical change is positively and significantly affected in agriculture, energy & manufacturing, and construction but slightly less in services. A similar pattern applies to scale efficiency, while technical efficiency only has a strong positive reaction in services. The Funds often have a negative impact on capital accumulation. The employment rate, however, is virtually unaffected by the Funds.

Different types of Structural Funds are found to have substantially different influences, with the European Social Fund arguably having the strongest impact. This is supported by the positive impact of the ESF on DOUTPN and DOUTPC. The ERDF, generally assigned very little significance, has some positive effects on capital growth in Services and the aggregate economy, in contrast to the other Funds. Indeed, the EAGGF and the ESF often negatively affect capital growth. Interestingly, the ESF also tends to negatively affect employment growth (not very significantly), and the EAGGF negatively affects virtually all of the variables in Construction. An obvious consequence of this finding is that analyses based on aggregate measures of the Structural Funds, obtained as a sum or a product of the three components, should be interpreted with caution.

More generally, the size of the impact of the Funds is not particularly large but is in line with the results obtained by Garcìa-Solanes and Maria-Dolores (2002a, b) and Aiello and Pupo (2007). Obvious caveats to these results concern the probable presence of measurement errors in the Fund variables. However, the diagnostic tests (available upon request) are generally satisfactory.

14.6 Concluding Remarks

In this chapter, we consider the European Structural Funds' impacts on convergence across Italian regions and the three waves of the Funds over the 1989–2006 period. We focus on Funds' effects on productivity and employment in the Italian regions, while separately considering the Funds' effects on four sectors (agriculture, manufacturing, construction, and services) of the regional economies. We use a non-parametric FDH-VP approach to calculate Malmquist productivity indexes.

Our evidence implies that the Funds had a weak, but significant, impact on total factor productivity change but virtually no effect (in particular, a positive one) on capital accumulation and employment. Different types of Structural Funds are found to have substantially different influences, with the European Social Fund, arguably, having the strongest impact. The failure to observe a strong impact of the Funds on productivity in Energy and Manufacturing may help to explain why Boldrin and

Canova (2001) do not obtain significant results for the regional economies when considered as a whole. However, we also believe that our empirical procedure allows for an improved treatment of the omitted variable and selection problems inherent to policy evaluation.

In future work, we plan to extend our data set to more recent years. Moreover, expanding on Arcelus and Arocena (2000), we wish to apply a different approach to the decomposition of productivity changes, consistent with the computation of annual measures. This will increase the power of our estimates and allows for a more traditional dynamic specification in our regressions. A puzzling feature of our estimates that we also wish to focus on in future work is the weak role of (national) capital account expenditures. Arguably, finer-grained expenditure classifications should be considered.

Furthermore, if one takes the view that growth in the Mezzogiorno regions is constrained by the scarce availability of certain local public goods, such as physical but also social, infrastructure,[16] one should both control for regional differences in these factors and ascertain whether their accumulation was influenced by the Structural Funds. An important attempt along the first of these research lines was provided by Ederveen et al. (2006): we believe that pursuing both of these avenues in the future is a high priority for the correct assessment of the Structural Funds' impact.

Appendix

The 20 administrative regions: order of presentation and territorial partition.

North	Centre	Mezzogiorno
(1) Piemonte	(9) Toscana	(13) Abruzzo
(2) Valle d'Aosta	(10) Umbria	(14) Molise
(3) Lombardia	(11) Marche	(15) Campania
(4) Trentino Alto Adige	(12) Lazio	(16) Puglia
(5) Veneto		(17) Basilicata
(6) Friuli Venezia Giulia		(18) Calabria
(7) Liguria		(19) Sicilia
(8) Emilia Romagna		(20) Sardegna

[16]Evidence in favour of this view is provided by D'Acunto et al. (2004).

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Chapter 15
Fostering the Self-Employment in Spain: An Evaluation of the Capitalisation of Unemployment Benefits Programme

Matías Mayor, Begoña Cueto, and Patricia Suárez

Abstract Self-employment has become an important source of employment in the last decades. Moreover governments have developed labour market programmes in order to foster self-employment. The capitalisation of unemployment benefits is a Spanish programme that gives the unemployed people the possibility to receive the contributory unemployment benefits in a lump sum payment in order to set up a business.

Our analysis supports the existence of spatial spillovers in regional labour markets; consequently, the model must include this spatial process explicitly. The results suggest that the magnitude of the direct effect is smaller but it is in accordance with the expected, since the possibility of capitalisation of unemployment benefits is not the main reason to move into the self-employment.

Keywords Self-employment • Active labour market policies • Evaluation

JEL Classification J23, J68, C21, R12

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15.1 Introduction

Self-employment has become an important source of employment in the last decades. Among the reasons that can explain the increase of self-employment, we can quote the promotion of this type of employment by governments. As a means to reduce unemployment, labour market programmes have been developed across Europe, and one of the most popular measures is self-employment subsidies for the unemployed. The purpose of this measure is to encourage unemployed people to start their own businesses.

The aim of this chapter is to evaluate the impact of the main self-employment programme in Spain: the capitalisation of unemployment benefits, a programme that gives the unemployed people the possibility to receive as a lump sum payment the contributory unemployment benefits in order to set up a business. We estimate the effects on unemployment using data from the Spanish Provinces during the period 2003–2009 using spatial econometrics techniques. Our purpose is to study this relationship for the Spanish case while considering the spatial dimension that, to the best of our knowledge, have not been previously considered in the literature. Also, the resulting reverse causality and endogeneity issues have been overcome as we explain below.

This chapter is set out as follows. Next section is dedicated to analyse the self-employment programmes. Section 15.3 explains the evolution of self-employment in Spain and the principal self-employment programme: the capitalisation of unemployment benefits. Sections 15.4 and 15.5 are devoted to the role of the space and the spatial panel data model which include the number of participants in the capitalisation of unemployment benefits programme. Finally, Sect. 15.6 provides a conclusion to the chapter.

15.2 Self-Employment Programmes

During the last two decades, governments have fostered self-employment as a means to combat unemployment. The principal aim of policies encouraging self-employment is increasing the number of transitions to self-employment and reducing the number of exits. The expenditure in this kind of active labour market policies is generally low (the average for the EU-15 is 0.043 of GDP in 2010[1]), but, in the case of Spain, there is a relevant programme since 1985, whose expenditure came to 0.20 % GDP in 1987–1991. In 2010, Spain is the country with the highest expenditure in this kind of measures, more than twice the average in the European Union. In this section, justifications for this kind of programmes are provided and a brief survey of the empirical evidence about their effects is done.

[1] See Table 15.5 in Annex.

15.2.1 Why Should Governments Promote Self-Employment?

First question to be addressed is why governments should support unemployed people to enter self-employment. The answer has two orientations: on the one hand, market failures and financial constraints and on the other hand, economic externalities.

With respect to market failures, some people have limited opportunities to become self-employed because of difficulties to access to finance. They are unable to obtain enough funding (or any funding) for what they believe are viable projects. In general, credit rating systems are based on personal characteristics, personal finance history and employment experience. Unemployed people—especially some groups, like young people or women—have fewer savings and greater difficulties to convince banks about the viability of the business proposition. So unemployed people faced financial constraints and, as a result, fewer unemployed people enter self-employment (or those who entered establish under-resourced businesses, with a greater likelihood of failure). Therefore, the existence of market imperfections leads to suboptimal distribution of finance (ILO 2002).

In this framework, governments can use different actions in order to counter imperfections arising in risk estimation. This is the case of regulation (against discrimination by reasons of gender, race and disability), subsidies and micro-finance support. However, neither theoretical models nor the empirical knowledge about the impact of government interventions provide convincing evidence regarding the benefits of these interventions (Parker 2004).

Second reason to foster self-employment is economic externalities by means of job creation. New self-employed people have potential small firms; they could create jobs and promote economic growth. During the last two decades, small firms have created jobs at a faster rate than larger firms (Storey 1994). This fact has justified programmes promoting new start-ups and incentives to small and medium enterprises. Nevertheless, several authors do not consider this reason as a justification because of the quality of created jobs, the characteristics of people who fill them and the indirect effects over large firms.[2]

15.2.2 Empirical Effects of Self-Employment Programmes

Evaluations of active labour market policies conclude that self-employment programmes usually have high deadweight and displacement effects. As Storey (1994) argues, these schemes may be relatively effective as labour market policies, but they tend to be relatively ineffective as policies aimed at stimulating and supporting the small business sector as a whole.

[2]More details in Storey (1994).

From a microeconomic perspective, several evaluations can be quoted. For a German programme, Pfeiffer and Reize (2000) compare survival rates and employment growth between granted self-employed people and non-granted ones finding that the bridging allowance scheme does not appear to have a job creation impact. For the same Reize (2004) obtains a lower growth rate for the subsidised enterprises. About the effects of loan guarantee schemes, the evidence in UK and USA reported by Parker (2004) points out that "while they do not do much obvious harm, they do not appear to do very much good either". Finally, Meager et al. (2003) evaluates a programme for young people in UK finding no statistical evidence of an impact of participants' subsequent employability. Contrary to these findings Baumgartner and Caliendo (2008) and Caliendo (2009) obtain positive effects of two start-up programmes to unemployed in East Germany. The results show that participants have lower unemployment rates, higher probabilities of being in self-employment and/or paid employment and higher income than non-participants.

From a macroeconomic point of view, there is little evidence about the impact of ALMP on self-employment, but Staber and Bögenhold (1993) show that self-employment programmes have a modest positive influence on self-employment rates, and Cowling and Mitchell (1997) suggest that the British government programmes—the Enterprise Allowance Scheme and the Loan Guarantee Scheme—are explanatory variables in the growth of self-employment in the UK during the 1980s.

The majority of start-up policies are targeted on increasing the inflows into self-employment. In fact, Meager (1992) states that "a more detailed examination of self-employment flows, and the factors influencing them, is also likely to be beneficial in the evaluation of labour market policies aimed at self-employment". The design of self-employment policies could improve with a better understanding of the relationship between inflows and outflows.

Román et al. (2013) state that the contribution of start-up programmes is ambiguous. They stress the need of considering the heterogeneity of self-employment (own-account workers and employers; opportunity and necessity entrepreneurs and innovative and imitative entrepreneurs) in the definition of policies. In this sense, for the case of Spain, Congregado et al. (2010) suggest that start-up incentives encouraging unemployed people to become own-account workers can only "reduce unemployment directly but not to create new employment".

Moreover, the economic situation should take into account given that "transitions to employer evolve pro-cyclically, whereas own-account work chances evolve counter-cyclically" (Román et al. 2013). This result implies the need of a better selection of participants in self-employment programmes in order to maximise job creation.

Another relevant issue is that policies fostering self-employment are targeted to unemployed people and a common result in the literature is the negative effect of unemployment on the self-employment survival (Millán et al. 2012; Muñoz-Bullón and Cueto 2011). Therefore, we can expect limited results from this kind of programmes.

In this sense, Shane (2009) concludes that instead of developing policies to increase the number of “typical entrepreneurs”, governments should identify the start-ups with the higher potential growth. Obviously, it is difficult to “pick-up the winners” but there are some conditions that can help in this task such as human capital, motivation or industry among others. Moreover, the evaluation of the programmes provides with useful information to take decisions about how to improve them in order to maximise their effects in terms of self-employment survival and job creation.

15.3 Self-Employment in Spain and the Capitalisation of Unemployment Benefits

Self-employment represents around 17 % of the total employment in Spain.[3] During the period 1986–2009, it increased by almost a million people. We can distinguish three periods in the self-employment rate: a decrease from 1989 to 1992, followed by an increase during 1993–1996 and another phase of decline. The increase in self-employment rate coincides with the increase in unemployment during the period 1992–1994 (after a decrease during the second half of the 1980s, the unemployment rate reached a maximum of 24.1 % in 1994). The decrease in the rate from 1995 onwards corresponds to the period of highest growth in employment. While the number of self-employed workers were around three million people (a maximum of 3.6 million in 2007), wage employment increases from nine million in 1997 to 16.8 million in 2007. As a consequence, the self-employment rate reduces (Fig. 15.1).

We know that changes in self-employment rate can be due to changes in self-employed people or in total employed people. And changes in the stock of self-employed people are the result of flows from and to self-employment. So we are going to focus on inflows and outflows. Inflows to self-employment are constant until 1992 and from then on there is an increase, reaching the maximum in 1996 (Table 15.1). The tendency changes again in 2004 reaching a new maximum in 2008, although this is due to a methodological modification, given that self-employed workers in agriculture are included in the Especial Regime for Self-employed Workers since this year.[4] Nevertheless, inflows decrease in 2009 and 2010 to increase again in the last 2 years. Outflows follow a similar tendency than inflows. We can highlight the growth after 2008, probably due to the economic crisis we face.

[3]For an analysis of self-employment in Spain, see Congregado et al. (2006).

[4]Previously, they have their own regime (only for agricultural workers).

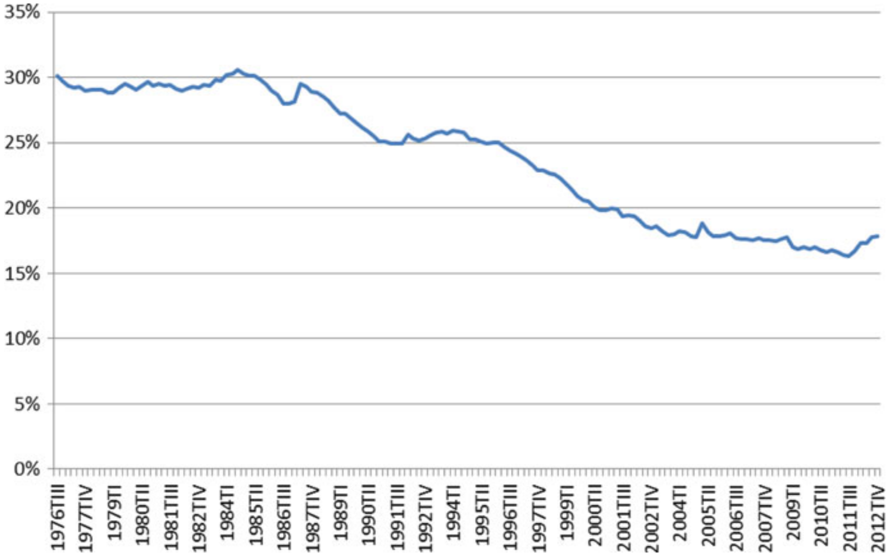

Fig. 15.1 Self-employment rate in Spain. *Source*: Labour Force Survey (LFS)

15.3.1 The Capitalisation of Unemployment Benefits

In 1985, the Spanish Government introduced the capitalisation of unemployment benefits. This programme gives the unemployed people the possibility to receive in a lump sum payment, the contributory unemployment benefits in order to set up a business. This is one example of activation measures because it consists in transforming the unemployment benefits, main passive policy, in a support to be used to start-up a business, i.e. to be employed. Participants have access to funding, reducing their potential financial constraints.

The amount of the lump sum payment depends on the unemployment benefits. Any unemployed individual who is entitled to receive unemployment benefits can capitalise them. Unemployment benefits can be paid for a maximum of 2 years and the amount is 70 % (60 % after 6 months) of the previous wage subject to a ceiling. Taking into account these issues, the lump sum payment is estimated.

Seven years later, in 1992, this programme was suppressed for the self-employed, and it was valid only for those unemployed people who entered cooperatives. The reasons for this change were: on the one hand, the financial deficit in the unemployment benefits system in 1990 that makes necessary the reduction in expenses and, on the other hand, the belief that the majority of the subsidised business had a high probability of failure (Toharia 1998). Moreover, it was generally agreed that the programme had been poorly designed and managed: there were no evaluations of the business' economic viability, the programme was carried out by

Table 15.1 Inflows to and outflows from self-employment and participants in capitalisation of unemployment benefits programme (thousands)

			Participants in capitalisation of unemployment benefits	
	Inflows	Outflows	*n*	% over inflows
1986	374.4	236.6	48.1	12.85
1987	305.5	259.9	53.1	17.38
1988	297.7	255.2	65.1	21.87
1989	285.3	265.0	74.3	26.04
1990	306.5	281.2	70.7	23.07
1991	283.2	281.9	75.4	26.62
1992	290.7	318.0	37.3	12.83
1993	360.6	345.7	0.6	0.17
1994	402.0	319.1	0.1	0.02
1995	423.0	371.2	0.1	0.02
1996	456.4	426.9	0.1	0.02
1997	422.0	380.7	0.0	0.00
1998	450.0	347.3	0.0	0.00
1999	442.6	384.5	0.0	0.00
2000	423.3	360.5	0.1	0.02
2001	394.2	362.7	0.1	0.03
2002	418.2	365.9	0.6	0.14
2003	452.7	356.3	20.9	4.62
2004	481.3	372.1	50.3	10.45
2005	475.0	369.0	78.9	16.61
2006	503.5	390.6	114.7	22.78
2007	542.9	371.0	143.5	26.43
2008	735.6[a]	552.5	153.9	20.92
2009	445.7	526.5	150.0	33.65
2010	487.5	498.9	145.6	29.87
2011	531.3	524.7	139.7	26.29
2012	503.5	390.6	138.1	27.43

[a]Methodological change in the Social Security records
Source: Ministerio de Trabajo y Asuntos Sociales (several years)

staff who were not specialised in creation of business, there was no selection of the projects and there was no evaluation system of the programme (OECD 1995).

However, in 2002, the option for self-employment was relaunched, although there were several changes with respect to 1985. Unemployed people can receive their unemployment benefits in order to pay the quotas to Social Security and the initial expenses of the business (a maximum of 20 % of the total amount).

So the programme has three stages. From 1986 to 1992, any unemployed person who had the right to unemployment benefits can enter the capitalisation programme in order to set up a business. From 1993 to 2001, this option was only valid to handicapped people or unemployed people entering cooperatives but not for all the unemployed people. Finally, in 2002, the programme is similar to the first stage. However, there have been several small changes in the last years related to requirements to enter cooperatives.

Focusing on the self-employment option, in the first period, 1986–1992, 424,047 people took part in the capitalisation programme, an annual average of 60,000 unemployed people. From 1992, the change in the programme reduced the participants to 100 persons every year (only disabled people). In 2002, latest change has increased the participants up to 150,000 individuals in 2009 (Table 15.1).

The programme had a successful result in terms of participation: during the period 1986–1992, a 19.8 % of people entering self-employment had access to the capitalisation of unemployment benefits. However, self-employment inflows increased notably while the capitalisation of unemployment benefits did not work for self-employment (except for handicapped persons), i.e. from 1992 to 2001.

We are going to focus in the last period of the programme (starting in 2003) and our last year of reference will be 2009. This period shows the greatest number of participants in the programme, in absolute terms, and also related to the number of inflows into self-employment.

15.4 Entrepreneurship and the Role of Space

Although entrepreneurship is a phenomenon of time and space, its spatial dimension has not always been considered. Plummer (2010) demonstrates that spatial dependence is "especially problematic for entrepreneurship research", as certain variables such as survival or start-up rates are especially prone to spatial dependence. The entrepreneurs' behaviour can be explained by their previous behaviour and by the experiences of other entrepreneurs in the same location. Spatial dependence becomes more relevant when entrepreneurial activity tends to be clustered geographically.

The explicit consideration of the spatial dimension in the analysis of entrepreneurship means accounting for not only the effect of entrepreneurship capital in a specific region *i* on the economic performance of that region but also the effect of entrepreneurship capital in neighbouring regions on the economic performance of region *i*. Pijnenburg and Kholodilin (2012) explain three arguments for the spatial dimension of entrepreneurship: (1) the difficulty in communicating knowledge in innovative industries makes direct interaction necessary; (2) innovative and knowledge-based entrepreneurial activity tends to cluster spatially (Audretsch and Feldman 1996) and (3) entrepreneurship capital increases competition, which leads to improvements in competitiveness and economic development.

The regional performance of the Spanish labour market has been studied from different perspectives using alternative methodologies. The most important stylised fact is the existence of fundamental differences in regional unemployment rates and their temporal persistence (Jimeno and Bentolila 1998; Bande et al. 2008, among others). The existence of these geographical differences may require that spatial issues are included in whichever model is selected, but few papers focus on the analysis of spatial processes in the Spanish labour market (Suárez et al. 2012; López-Bazo et al. 2002; Alonso-Villar and Del Río 2008). A review of the international literature also reveals a limited number of papers that focus on spatial aspects (e.g. Molho 1995; Overman and Puga 2002; Patacchini and Zenou 2007; Patuelli et al. 2012).

These studies find evidence on the existence of a spatial autocorrelation process among the unemployment rates, and hence, for any model to be capable of explaining or analysing the performance of the (regional) labour markets, it must include these processes. This evidence was reinforced by theoretical contributions. Patacchini and Zenou (2007) reflect on the causes of this spatial autocorrelation process and provide a simple model where individuals engage in job search processes outside their residential areas generate the spatial relationships between areas.

Collecting these theoretical arguments, the most adequate econometric specification may be a Spatial Durbin Model, which includes a spatial lag of the dependent variable (the unemployment rate) and a spatial lag of the explanatory variables (capitalisation of unemployment benefits).

In this chapter, a panel data structure is used that provides improved modelling potential than the cross-sectional approach applied in previous works. Elhorst (2010a, 2012) summarises the recent contributions on the specification and estimation of static and dynamic spatial panel data models. Moreover, it is possible to distinguish two different strategies for selecting the spatial econometric model. The first option is known as the specific-to-general approach and consists of testing whether there is spatial autocorrelation in the OLS residuals obtained from a non-spatial model and proposing a spatial lag or spatial error specification. This strategy is described by Florax et al. (2003) and is based on the Lagrange Multiplier tests and their robust version (Anselin et al. 1996). This is the most common alternative applied in empirical studies.

The other option proposes an initial model that is the most complete option. There are a series of simpler models, which are special cases, nested within this model that ideally should represent all of the alternative economic hypotheses requiring consideration. Its specification may include three different types of interaction effects (Manski 1993) distinguished when the economic variable studied in one location could be influenced by the behaviour of its neighbouring locations. These effects are: (1) *endogenous* interaction effects, where the decision of a spatial unit depends on the decision taken by other spatial units; (2) *exogenous* interaction effects, where the decision of a spatial unit to behave a certain way depends on the independent explanatory variables of the decisions taken by other spatial units and (3) *correlated effects*, where similar unobserved environmental characteristics result in similar behaviour.[5]

[5]There is no theoretical support for the third type of effects. This effect collects omitted factors in the model that are supposed to be spatially autocorrelated.

The most complete model (called the Manski model by Elhorst 2010b) may be captured by the following expression with spatial and time-period specific effects:

$$Y_t = \rho W Y_t + \alpha i_N + X_t \beta + W X_t \theta + \mu + \xi_t i_N + u_t$$

$$u_t = \lambda W u_t + \varepsilon_t$$

where Y_t denotes an ($N \times 1$) vector consisting of one observation of the dependent variable (the unemployment rate for every spatial unit ($i = 1, \ldots, N$) in the sample at time t ($t = 1, \ldots, T$), and X_t is an $N \times K$ matrix of exogenous explanatory variables. The $N \times N$ matrix W is a non-negative matrix of known constants describing the spatial arrangement of the units in the sample. Its diagonal elements are set to zero by assumption, as no spatial unit can be viewed as its own neighbour. The $k \times 1$ vectors β and θ collect the response parameters of the exogenous explanatory variables and their spatial lags in the model. ρ is the spatial autoregressive coefficient, and λ is the spatial autocorrelation coefficient.

The $N \times 1$ vector u contains the spatial-specific fixed effects to control for all spatial-specific, time-invariant variables, the omission of which could bias the estimates in a typical cross-sectional study (Baltagi 2005), and ξ_t ($t = 1, \ldots, T$) collects time-fixed effects to control for all time-specific, unit-invariant variables, the omission of which could bias the estimates in a typical time-series study.

15.5 Estimation Results

The main aim of the chapter is to obtain evidence concerning the nature of the relationship between unemployment and the Spanish capitalisation programme from a macro-regional perspective; hence, the unemployment rate is introduced as a dependent variable. We consider as explanatory variables: the proportion of women (LFS), the distribution of educational attainment in the population (LFS), industries' employment shares (LFS) and the capitalisation of unemployment benefits. This variable is the number of participants in the capitalisation programme over the unemployment stock in each province (*capitalisation* variable). Therefore, an increase in the number of participants in the capitalisation programme results by construction in a reduction in unemployment rate, *ceteris paribus*. Also, any change in the number of unemployed people has a feedback effect on the capitalisation ratio. This could lead to endogeneity from reverse causality. These issues have been overcome following the strategy adopted by Baltagi et al. (2012) and instrumented for the capitalisation ratio using their lagged values.[6]

[6]See Bell et al. (2002).

Table 15.2 Specification tests

LMlag	LMerr	R-LMlag	R-LMerr	$H_0 : \theta = 0$	$H_0 : \theta + \rho\beta = 0$
273.8624***	170.5543***	106.5860***	3.2779*	46.7355***	49.8135***

Note: ***, ** and * denote significant at 1 %, 5 % and 10 %, respectively

Due to the proposal specification, it is necessary to determinate whether the spatial and/or time effects can be considered fixed or random. From a theoretical perspective, Elhorst (2012) analyses what happens when one alternative is preferred to the other and reaches the conclusion that many studies fail to pay sufficient attention to the justification for employing a random effects approach. In any case, the adoption of random effects may be inadequate when the spatial data covers all provinces. In this situation, Beenstock and Felsenstein (2007) and Nerlove and Balestra (1996), among others, note that spatial and/or time-fixed effects may be adopted, as the values of the variables in each spatial unit are not obtained randomly. A Hausman test is conducted to test the random effects model against the fixed effects models, and the results suggest that the fixed effect models are appropriate (27.372 with 13 freedom degrees).[7]

The likelihood ratio test (LR) is performed to determine whether the spatial-fixed effects are jointly insignificant, and this hypothesis is rejected (156.547 with 47 degrees of freedom). These empirical results indicate that a spatial-fixed effects panel data model is preferable. To conclude the identification stage, we have to select the most appropriate spatial specification. Once the model has been estimated by OLS, we use the LM test and its robust version to determine whether a spatial lag or spatial error specification is preferable. Whenever OLS is rejected in favour of any spatial alternative, the spatial Durbin model should also be estimated and compared (using LR test) with the alternative models. The results are summarised in Table 15.2 using contiguity criteria to construct the spatial weights and indicate that the spatial Durbin model is the most appropriate to fit the data.

As the explanatory variables are in logs and the dependent variable in our model is the logged level of unemployment rate, the coefficient estimates can be interpreted as elasticities (Table 15.3). However, the coefficient in the Spatial Durbin Model cannot be interpreted directly; hence, we need to obtain the direct and indirect effects.

Following LeSage and Fisher (2008), we have to bear in mind that the dependent variable (unemployment rate) in each region i using an SDM depends on: the share of unemployment in the regions neighbouring i (captured by the spatial lag), the characteristics of the provinces captured by the control variables (X) and the characteristics of neighbouring regions captured by the spatial lag variables (WX). It is necessary to capture all of these relationships to appropriately interpret the estimation outcomes. Two different effects appear: direct and indirect effects.

[7]This value is obtained including spatial-fixed effects. The same conclusion is reached with both time- and spatial-fixed effects.

Table 15.3 Estimation results of unemployment rate with spatial-fixed effects (Spatial Durbin Model)

	Model I	Model II
Female	−0.273 (−0.372)	−0.519 (−0.713)
Capitalisation	−0.188*** (−4.568)	−0.178*** (−4.320)
Industry	−0.091 (−1.208)	−0.098 (−1.301)
Construction	−0.166* (−1.177)	−0.177* (−1.837)
Secondary	–	0.014 (0.123)
University	–	−0.004 (−0.028)
Lag.Female	−0.402 (−0.239)	−0.889 (−0.529)
Lag.Capitalisation	0.123*** (2.718)	0.174*** (3.657)
Lag.Industry	−0.364** (−2.275)	−0.479*** (2.947)
Lag.Construction	−0.434*** (−2.894)	−0.642*** (−3.951)
Lag.Secondary	–	−0.823*** (−2.605)
Lag.University	–	−0.856** (−2.381)
Lag.Unemployment rate	0.760*** (20.356)	0.725*** (18.190)
Sigma^2	0.0146	0.0141
R^2	0.9337	0.9358
Log-likelihood	194.2512	201.7878

Note: ***, ** and * denote significant at 1 %, 5 % and 10 %, respectively

The direct effect refers to the average response of the dependent variable to the independent variables, including feedback influences from impacts passing through neighbours and back to the region itself. The indirect effect reflects the effect that any change in a region has on the others and how changes in all regions affect a given region.

These complex interactions are calculated using the scalar measures proposed by Lesage and Pace (2009). These effects are reported in the bottom rows of Table 15.4. The direct effect of the *capitalisation* variable is negative and statistically significant in all cases. Because the unemployment rate and the capitalisation variable are both in logs, the direct impact can be interpreted as elasticity; if the *capitalisation* variable increases by 1 % in province *i*, the unemployment rate decreases by 0.196 % (Model I)/0.165 % (Model II), *ceteris paribus*.

The magnitude of the effect is smaller but it is in accordance with the expected, since the possibility to capitalisation of unemployment benefits is not the main reason to move into the self-employment. This kind of programme usually has a high deadweight effect, meaning that the majority of people who accede to the programme would be self-employed although they did not receive the subsidy (Meager 1996). In fact, the programme can be more useful facilitating the survival of the business than promoting the transition from unemployment to self-employment. Given that this decision can be less influenced by the existence of the programme; the subsidy can give an economic support during the first months when the

Table 15.4 Direct (DE), indirect (IE) and total effects (TE) in Model II

	Direct effect		Indirect effect		Total effect	
	Model I	Model II	Model I	Model II	Model I	Model II
Female	−0.451(−0.394)	−0.949(−0.830)	−2.302(−0.309)	−4.537(−0.699)	−2.753(−0.328)	−5.486(−0.738)
Capitalisation	−0.196***(−5.090)	−0.165***(−4.290)	−0.081(−0.944)	0.153(1.611)	−0.277***(−3.289)	−0.012(−0.122)
Industry	−0.230**(−2.321)	−0.272***(−2.810)	−1.700(−2.702)	−1.858***(−3.262)	−1.930(−2.774)	−2.130***(−3.362)
Construction	−0.343***(−3.551)	−0.415***(−4.021)	−2.159***(−4.939)	−2.572***(−6.415)	−2.503***(−5.333)	−2.988***(−6.853)
Secondary		−0.236(−1.317)		−2.766**(−2.392)		−3.002**(−2.311)
University		−0.189(−1.119)		−1.984**(−2.539)		−2.173**(−2.454)

Note: ***, ** and * denote significant at 1 %, 5 % and 10 %, respectively probability of failure is higher. Some participants may find the survival of the business very difficult, which limits the impact on unemployment rates. In this sense, it should be noted that the estimated direct effects for industries' employment shares (*industry* and *construction*) are higher in size to the estimated coefficient for capitalisation.

Turning to the indirect impacts, we note that there are discrepancies between these effects and the model coefficients on the spatially lagged variables. Therefore, if the coefficients of the spatially lagged variables were interpreted as an indicator of the size and significance of the spatial spillover, we would make an important error.

The indirect effect of capitalisation participants is negative but not statistically significant (−0.081) in Model I which does not include education variables. This result means that if the number of capitalisation participants over the unemployment stock grows in other provinces (*j*), the unemployment level decreases in province *i*. This is one of the interpretations of the indirect impact. A second interpretation of the indirect impact captures the cumulative impact of a change in one independent variable in region i averaged over all other regions. Therefore, increasing the *capitalisation* variable by 1 % in region *i* exerts a limited influence on each neighbouring province, but the cumulative effect over all municipalities decreases by 0.081 %.

With respect to the other variables, the results conform to the previous results obtained in the literature. The estimated indirect effect for industry and construction are negative and statistically significant too. In both cases, the size of the estimated coefficients is higher than the coefficient associated to the spatial lag of these variables. In Model II, the entrepreneurial capital is included considering as explanatory variables the distribution of the educational attainment of the population (*secondary* and *university*[8]) with the aim to control all possible variations that may affect the unemployment rate level.

Finally, the total impacts (size and significance) are analysed. In general terms, the results indicate that the estimated coefficient for the *capitalisation* variable is negative and statistically significant different from zero when the Model I (without educational attainment) is estimated. This outcome could be interpreted as evidence in favour of a slightly positive result of this type of programme since it would be responsible for a (small) reduction of the unemployment rate. If the *capitalisation* variable increases by 1 % in province i, the unemployment rate decreases by 0.277 %, *ceteris paribus*.

[8]The percentage of population with primary studies is not introduced in order to avoid multicollinearity.

15.6 Conclusions

In this chapter, we have considered the relationship between unemployment rate and the capitalisation of unemployment benefits programme. Self-employment represents a relevant proportion of employment in Spain. Moreover, there is a relevant programme fostering unemployed to enter self-employment. The capitalisation of unemployment benefits was launched in 1985, finished in 1992 and relaunched in 2002. Around 20 % of the annual inflows to self-employment took part in the programme.

We have used data from the Spanish provinces during the period 2003–2009 in order to evaluate the impact of this programme on the unemployment rate. As discussed earlier, Plummer (2010) demonstrates that spatial dependence is "especially problematic for entrepreneurship research". Thus, in this investigation, we have worked with a spatial Durbin model which is the most appropriate to fit the data.

The results suggest that the magnitude of the direct effect is smaller but it is in accordance with the expected, since the possibility to capitalisation of unemployment benefits is not the main reason to move into the self-employment. As noted above, this kind of programmes usually has a high deadweight effect, meaning that the majority of people who accede to the programme would be self-employed although they did not receive the subsidy (Meager 1996). Given that this decision can be less influenced by the existence of the programme, the subsidy can give an economic support during the first months when the probability of failure is higher. Some participants may find the survival of the business very difficult which limits the impact on unemployment rates.

Román et al. (2013) conclude that start-up incentives have a positive effect on self-employment likelihood, especially in periods of low unemployment. Following this line of reasoning, policy makers (at national and/or regional level) should develop the provision of tailored self-employment assistance and identify the individual entrepreneur's need. In fact, the programme can be more useful facilitating the survival of the business than promoting the transition from unemployment to self-employment.

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Annex

Table 15.5 Expenditure in self-employment programmes (% GDP)

	2003	2004	2005	2006	2007	2008	2009	2010
Spain	0.043	0.034	0.051	0.078	0.088	0.094	0.099	0.117
Poland			0.027	0.037	0.047	0.059	0.084	0.100
Greece	0.035	0.055	0.001	0.023	0.030	0.008	0.094	0.096
Slovakia		0.018	0.048	0.045	0.041	0.055	0.068	0.081
Germany	0.086	0.131	0.090	0.119	0.077	0.068	0.069	0.078
France	0.005	0.004	0.004	0.010	0.026	0.032	0.039	0.055
UE-27			0.032	0.040	0.033	0.033	0.037	0.044
UE-15	0.033	0.042	0.033	0.041	0.034	0.033	0.037	0.043
Finland	0.011	0.015	0.019	0.019	0.018	0.019	0.022	0.023
Sweden	0.036	0.033	0.034	0.029	0.016	0.013	0.012	0.023
Estonia	0.005	0.004	0.005	0.003	0.001	0.004	0.016	0.020
Italy	0.049	0.053	0.051	0.042	0.028	0.024	0.020	0.020
Hungary	0.007	0.005	0.005	0.003	0.004	0.006	0.006	0.009
Austria	0.005	0.004	0.005	0.005	0.005	0.005	0.006	0.007
Belgium	0.004	0.004	0.003	0.003	0.004	0.004	0.004	0.004
Czech Republic	0.005	0.005	0.004	0.004	0.003	0.003	0.004	0.004
Portugal	0.003	0.003	0.002	0.002	0.002	0.002	0.002	0.004

Source: European Communities (several years)

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Chapter 16
Regional Price Indices and Real Wage Equalization in Poland

Bartłomiej Rokicki

Abstract The goal of this chapter is an empirical verification of the hypothesis concerning the real wage equalization among different regions in the case of transition countries. In particular, we focus on Polish NUTS2 regions and for the first time, we apply regional PPP deflators in order to prove whether they may influence the results of the convergence analysis.

The issues concerning the evolution of regional labor market disparities within Central and Eastern European countries have been thoroughly discussed in many papers. Still, most of them have focused on the persisting differences in the regional unemployment rates. At the same time, the dispersion of wages across different locations and its evolution over time has been considered as one of the possible factors influencing spatial unemployment rate differentials. Less attention was though paid to the analysis of regional wage equalization process per se.

Up to now, the existing studies were based on wage data expressed either in current prices or constant ones but with price deflators calculated at the level of state. Here, we find that the application of regional PPP deflators significantly decreases the overall level of wage disparities across Polish regions (as compared to nominal wages). Nevertheless, it does not significantly change the overall pattern of their evolution. Hence, there is a tendency toward regional real wage divergence rather than equalization.

Keywords PPP • Regional convergence • Spatial unemployment differentials • Poland

JEL Classification E31, J31, R1

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16.1 Introduction

The issues concerning the evolution of regional labor market disparities within the Central and Eastern European countries have been thoroughly discussed in many papers. Still, most of them have focused on the persisting differences in the regional unemployment rates. At the same time, the dispersion of wages across different locations and its evolution over time has been considered as one of the possible factors influencing spatial unemployment rate differentials. Much less interest is put on the questions related to the evolution of regional wages per se, while in fact, it seems interesting since the average may be used as an indicator of regional income instead of commonly used *per capita* GDP.

Traditionally, the reasons behind the persistence of high unemployment rates in certain areas of the transition countries were found within the framework of neoclassical models of regional unemployment or the optimal speed of transition model (e.g., Ferragina and Pastore 2008). Yet, more recently there are a growing number of studies that rely on the factors related to agglomeration, such as economies of scale or externalities, to claim that this phenomenon may be in fact the result of a market failure (e.g., Pastore 2012). Under the latter approach, large regional wage differentials may lead to further reinforcement of existing unemployment disparities, since the inflow of workers coming to the areas offering higher real wage will improve their production capacity.

The role of wages in the agglomeration process has been thoroughly discussed particularly in theoretical papers following the ideas disclosed by Krugman within his New Economic Geography approach (Krugman 1991). The main message is that once the industry concentrates geographically, there must be an increase in regional wage disparities. The reason is that real wages decrease with a distance from industry centers due to both a decline in nominal wages and an increase in price index. Yet, in another paper, Krugman and Livas Elizondo (1996) argued that although closed markets promote huge central metropolises and lead to a rise in regional wage differentials, open markets should discourage them. Hence, we should observe the existence of the nominal wage differentials, while real wage differentials are supposed to be equalized.

The hypothesis concerning the impact of trade liberalization on regional real wage equalization was then empirically verified by Hanson (1997) who analyzed the effect of trade reform on regional wages in Mexico. Other studies dealing with the evolution of regional wage disparities in Europe include analyses for Germany (e.g., Kosfeld and Eckey 2010), Italy (e.g., Manacorda and Petrongolo 2006), Portugal (e.g., Pereira and Galego 2011), Spain (e.g., Motellón et al. 2011), or the UK (e.g., Dickey 2007). In case of the transition countries, we may find papers on the Czech Republic (e.g., Moritz 2011), Hungary (e.g., Kertesi and Köllõ 1999), Poland (e.g., Rokicki 2007), or Slovakia (e.g., Uramová and Kožiak 2008).

Almost all of the aforementioned studies, despite many methodological differences, share one common feature. It is that they do not take into account possible differences in the level of prices and the inflation rates between different regions within the same country. As a result, they do not show the real level of wages (and its evolution) which depends on the purchasing power of the regional per capita income. The latter may in fact differ substantially, especially in case of metropolitan and peripheral areas. Therefore, the real level of regional wage disparities may be lower than commonly believed, while the lack of convergence or the existence of divergence may be the consequence of statistical measurement error.[1]

This chapter investigates the possible impact that the inclusion of regional PPP deflators may have on the results of the analysis of regional wage differentials. In particular, it verifies the real wage equalization hypothesis in the case of Poland between 2000 and 2011 and shows what happens to the level of regional income disparities and their evolution over time once we apply regional PPP deflators instead of average deflators for the country as a whole. The case of Poland seems interesting not only because of its transition country status but also because of the fact that this is an example of a state which liberalized its trade policy during the accession negotiations with the EU.

The remainder of the chapter is organized as follows. In the next section, we summarize main findings concerning the evolution of regional labor markets in transition countries, in terms of regional wage disparities. Here we put special attention to the theoretical predictions for regional structure of wages and their empirical verification. Then we describe the methodology for the calculation of regional PPP deflators and possible problems with its application. In Sect. 16.4, we discuss the results of empirical analysis devoted to the evolution of regional real wage disparities in Poland between 2000 and 2011. Finally, we summarize our findings in the concluding section.

16.2 Literature Review

As argued in the previous section, most of the papers dealing with the issue of regional imbalances on the labor market in transition countries focus on persistent disparities in the unemployment rate. Although the reasons behind the existence of such differentials used to be analyzed within the neoclassical or the optimal speed of transition theoretical frameworks, the tendency observed lately is to explain them relying on models related to agglomeration economies and the New Economic Geography in particular. Here, authors such as Egger and Seidel (2008), Epifani and Gancia (2005), Francis (2009), Südekum (2005), or Zierahn (2013) show that regional unemployment and wage disparities result from differentials on regional goods markets. The latter, in turn, arise endogenously through the interplay of increasing returns to scale, transport costs, and interregional migration.

[1]According to the economic theory, areas with higher growth rate should tend to have higher inflation as well.

In particular, Epifani and Gancia (2005) introduce regional labor markets into the framework of the New Economic Geography, assuming flexible wages and labor market rigidities in the form of job matching. They prove that interregional labor migration triggers convergence in unemployment rates only initially, leading to a reduction of the unemployment pool in high unemployment regions and causing an increase of labor supply in low unemployment regions. Yet, after this initial impact, new immigrants contribute to an increase in the market potential of the receiving region, which in turn raises the productivity of any economic activity there. Circular causation process causes further expansion in labor demand that reduces again the local unemployment rate below the national average. Hence, worker reallocation may be in fact negatively correlated with regional unemployment.

Francis (2009) makes an extension to the above model by endogenizing the job destruction rate. Here, agglomeration process attracts new immigrants to the core region and leads to higher rates of both job creation and job destruction. It also leads to lower rates of unemployment by increasing productivity in the core. This suggests that the regional effects of job creation on unemployment dominate those of job destruction, which seems to be consistent with empirical evidence.

Finally, Zierahn (2013) introduces into the new economic geography framework efficiency wages and thus a wage curve. He shows that symmetric long-term equilibrium is given by equal regional unemployment rates that result from the real wage equalization. This assumption has been already presented in other new economic geography models (e.g., Baldwin et al. 2003), which in most of the cases support full employment, thus completely ignoring the possibility of unemployment. Yet, once a core–periphery structure occurs, unemployment is lower and wages are higher in the core compared to the periphery. As usual, for the new economic geography models, the stability of different equilibriums depends on the level of transport costs—in this case, symmetrical equilibrium is stable for high level of transport costs only. This may change though once we introduce congestion costs that influence migration decisions. It is possible then that for certain values of model parameters, higher degree of trade openness may in fact lead to a gradual equalization of real wages (and unemployment rate) as suggested already by Krugman and Livas Elizondo (1996).

The hypothesis concerning regional real wage equalization was empirically verified in a number of papers. Hanson (1997) was the first to test empirically the predictions of the New Economic Geography model. He analyzed the effects that trade reform introduced in the 1980s[2] had on regional wages in Mexico by studying both the pre- and post-trade reform regional wage structure. Hanson's study provided empirical evidence that the states with highest wages were located near Mexico City or along the US–Mexico border. However, testing for the effect of trade reform, he found only weak evidence of a compression in regional wage differentials following liberalization in trade policy.

[2] In the 1980s, Mexican government opened the economy to foreign trade and investment.

In the case of Europe, Kosfeld and Eckey (2010) show that although regional policy provided large amounts of funds to promote a catch-up of peripheral regions in Germany, disparities in wages have virtually not changed during the period 1995–2004, at the level of districts. Furthermore, they prove the relevance of economic geography in explaining the spatial structure of wages. These results may in turn explain the existing differentials in unemployment rate, since Südekum et al. (2005) find that regional differences in employment growth for eastern German districts are much more influenced by overly high regional wages than differences in the qualification, firm size, or industrial structures.

Interesting results may be found in the paper of Manacorda and Petrongolo (2006), who show that in the case of Italy, in spite of huge disparities in unemployment rate, there is a convergence of wages between southern and northern regions between 1977 and 1998. Although the Northern workers earn on average higher wages than Southern workers, the raw differential fell from 12 percentage points in 1977 to about 6 percentage points in 1998. Hence, they claim that the centralized wage-setting mechanism should be recognized as an important factor explaining the labor market dualism of the Italian economy. Still, the bulk of the regional mismatch results from an excess of labor supply in the South cannot be offset by labor outflows due to the low migration rate observed in the last decades.

The tendency toward convergence of regional wages cannot be confirmed in other Mediterranean countries such as Portugal or Spain. In particular, Pereira and Galego (2011) find important and stable regional wage differentials among Portuguese NUTS2 regions between 1995 and 2002. They show that estimated differentials between Lisboa and the rest of regions, range from about 20 % to 30 % and may be explained to great extent by differences in skills, occupational structure, and the share of large firms. Still, a substantial fraction of the estimated wage differential arises as a result of differences in rewards for workers with equal level of skills. Similar results are reported by Motellón et al. (2011) in their analysis of regional wage disparities among Spanish NUTS2 regions between 1995 and 2002. Here, they also find that spatial equalization of human capital endowments alone would not automatically remove real wage differentials since identical workers in identical jobs and identical firms receive different wages depending on the region in which they are located.

Dickey (2007) focuses on intra-regional wage differentials in the UK and shows that the patterns in regional earnings were characterized by greater regional inequality during the 1970s and 1980s and convergence in regional average earnings during the 1990s. Yet, she claims that the convergence in regional average earnings in the early 1990s occurred mainly due to the recession whose results were more harmful for more developed, southern regions of Great Britain. Moreover, the fall of inequality between regions was accompanied by an increase of inequality within the regions.

Special attention should be put upon empirical papers dealing with the issue of regional wage differentials in the transition countries. In their case, regional wages can be influenced both by undergoing transformation process and the trade liberalization, which started in the 1990s (manufactured goods) and concluded in

2004 (agricultural goods) at the time of accession to the European Union. Here, Moritz (2011) finds that wages for the lowest skill category of workers in the NUTS4 regions placed at the western Germany (Bavaria) border or Austrian border increased substantially between 1996 and 2002 as compared to the wages of workers in non-border areas. Yet, completely opposite trend may be observed for all other skill groups; thus, overall there is a tendency toward divergence of regional average wages rather than convergence.

Kertesi and Köllõ (1999) analyze the change in the spatial structure of wages in Hungary between 1986 and 1996. They find that there was an increase of regional wage disparities until 1992 and a fall afterwards. Still, the wage gaps implied by the observed unemployment rate differentials holding other wage determinants between the best and the worst regions widened from about 7 % in 1989 to 25 % in 1996. The authors also claim that estimated elasticities of wages with respect to regional unemployment hint at a relatively high degree of wage flexibility as compared to other transition countries. This means that there were in a range typical of mature market economies already in 1992–1993.

Rokicki (2007) examines the evolution of average monthly wages in Polish former 49 voivodships and new 16 NUTS2 regions between 1980 and 2004. In both specifications, he proves the existence of small decrease in dispersion of regional wages before 1990 and its increase afterwards, which is related to the ongoing agglomeration process. It is noteworthy that his results are different from the ones obtained by Egger et al. (2005), who found significant regional wage convergence in Poland during the 1990s. Finally, the overall increase in regional disparities of average monthly wages, in transition countries, is confirmed also by Uramová and Kožiak (2008) who analyze the evolution of wage differential across Slovak NUTS3 regions between 1998 and 2006. In their opinion, this process is also triggered by spatial concentration of economic activity, especially in the capital region.

The general conclusion, which can be drawn from the above studies, is that there is no one pattern in the evolution of regional wage disparities in Europe. In several countries, we find signs of ongoing divergence process (especially in the case of the transition countries); in other, the existing differentials seem to be stable over time. We cannot observe through any example of tendency toward regional real wage equalization as suggested in several New Economic Geography theoretical models.

Still, one major problem arises while analyzing the results of all previous empirical studies. It is that none of them applies regional PPP deflators, which means that, in fact, they do not take into account the differences in regional price indices.[3] This may lead to serious biases since it is proven that high nominal wages reflect to some extent high regional prices (e.g., Tabuchi 2001). This is particularly visible once we compare rural and metropolitan areas and, as a matter of fact, is contrary to the theoretical predictions of the majority of New Economic Geography models.

[3]Although it should be mentioned that Kosfeld and Eckey (2010) try to deal with this problem including in their estimations, different assumptions regarding price level and wage equalization.

Still, one should take into account, the most of them do not include immobile goods prices within the regional price index.

The issue of the impact that the differences in regional price indices may have on the results of analyses concerning distribution or evolution of regional wages has been addressed in several papers. The contribution by Blien et al. (2009) may serve as a good example here. They apply Multiple Imputation method to estimate regional price differences for western Germany relying on the data from few surveys showing regional price levels for 32 small regional units. They show then that the application of imputed price levels significantly change the results of the estimations concerning the agglomeration wage differentials.

This chapter adds to the existing literature by showing the results of calculations concerning regional PPP deflators in Poland at the NUTS2 level and their impact on the analysis of regional wage differentials. Due to the limitations of space, we concentrate on two main questions only. First, we want to empirically verify theoretical previsions concerning regional price indices and possible differences between core and periphery regions in this aspect. Second, we want to examine the evolution of regional real wage disparities in order to show whether there was a trend toward regional real wage equalization in Poland between 2000 and 2011.

16.3 Research Methodology

The lack of studies concerning regional wage differentials, which rely on regional PPP deflators, cannot be really surprising. The main problem here is the absence of necessary statistical data on regional prices. For this motive, we focus on Poland, where such data is available for 16 regions at the NUTS2 level since 2000 onwards. In any case, Poland also seems interesting as a country belonging to the group of transition economies, which has been a subject of many analyses within the last two decades.

Regional PPP deflators are estimated in accordance to the common Eurostat/OECD methodology. Although it is used to allow income comparisons between different countries, it may also be applied in order to compare real income level between different regions within the same state. It is based on the expenditure side of the Gross Domestic Product and employs the EKS (Éltetö-Köves-Szulc) method that requires data concerning both the prices of representative goods and services and the structure of spending (that is required to weight price indices calculated for particular base categories).[4]

In the first step, we apply data concerning prices at the base category level to calculate unweighted PPP indices for each pair of regions. These are so-called Fisher type PPP that rely on Laspeyres index for products representative for the first region and Paasche index for products representative for the second one. The above indices

[4] See European Communities/OECD (2006) for more details.

are defined as follows:

$$L_{\mathrm{AB}} = \prod_{i \in R_{\mathrm{A}}} \left[\frac{P_{i\mathrm{A}}}{P_{i\mathrm{B}}} \right]^{\frac{1}{n_{\mathrm{A}}}} \tag{16.1}$$

where R_{A} stays for products representative for region A

$$P_{\mathrm{AB}} = \prod_{i \in R_{\mathrm{B}}} \left[\frac{P_{i\mathrm{B}}}{P_{i\mathrm{A}}} \right]^{\frac{1}{n_{\mathrm{B}}}} = \frac{1}{L_{\mathrm{BA}}} \tag{16.2}$$

where R_{B} stays for products representative for region B

$$F_{\mathrm{AB}} = \sqrt{L_{\mathrm{AB}} P_{\mathrm{AB}}}. \tag{16.3}$$

Still, the Fisher type PPP does not accomplish the transitivity condition which is achieved by applying the EKS method. The EKS PPP between regions j and k can be computed using the following formula:

$$\mathrm{EKS}_{jk} = \left| F_{jk}^2 \times \prod_{l \neq j,k} \frac{F_{jl}}{F_{kl}} \right|^{\frac{1}{n}} \tag{16.4}$$

where j, k, $l \in N$.

Finally, we need to standardize the EKS indices in order to get PPP deflators that have a group of regions as a basis. We achieve this by calculating.

$$\mathrm{EKS}_A = \frac{\mathrm{EKS}_{AA}}{\left(\prod_{i=A}^{n} \mathrm{EKS}_{iA}\right)^{\frac{1}{\sum i}}} = \frac{\mathrm{EKS}_{AB}}{\left(\prod_{i=A}^{n} \mathrm{EKS}_{iB}\right)^{\frac{1}{\sum i}}} = \cdots = \frac{\mathrm{EKS}_{An}}{\left(\prod_{i=A}^{n} \mathrm{EKS}_{in}\right)^{\frac{1}{\sum i}}}. \tag{16.5}$$

Standardized PPP deflators at the base categories must be then aggregated using weights for particular base categories in the overall expenditure. This is done in a similar way as described for particular base categories. Hence, first we compute the Laspeyres index defined as:

$$\overline{L_{\mathrm{AB}}} = \frac{\sum_{i=1}^{n} \frac{\mathrm{EKS}_{i\mathrm{A}}}{\mathrm{EKS}_{i\mathrm{B}}} \times E_{i\mathrm{B}}}{\sum_{i=1}^{n} E_{i\mathrm{B}}} \tag{16.6}$$

where E stays for expenditure in base category i in region B.

Then we calculate Paasche and Fisher indices, following the formulas:

$$\overline{P_{\mathrm{AB}}} = \frac{1}{\overline{L_{\mathrm{BA}}}} \tag{16.7}$$

$$\overline{F_{\mathrm{AB}}} = \sqrt{\overline{L_{\mathrm{AB}}}\,\overline{P_{\mathrm{AB}}}}. \tag{16.8}$$

Finally, we apply the EKS method in order to meet the transitivity condition and standardization in accordance with the Eqs. (16.4) and (16.5). This way we get the average PPP deflators for each region. These deflators are afterwards used to adjust the data on regional average monthly wages.

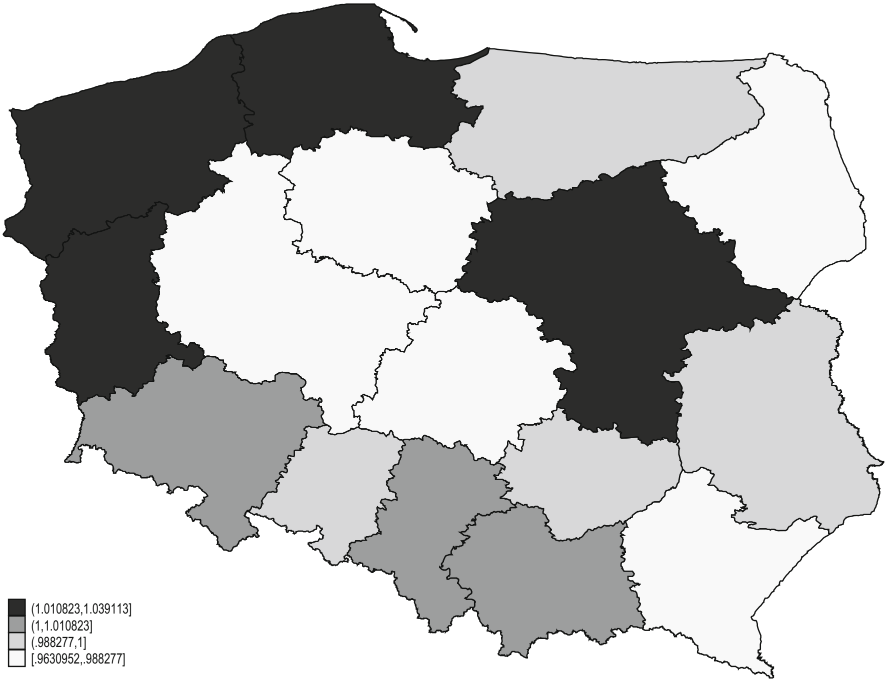
All the necessary data come from the different publications of the Polish Central Statistical Office and covers the 2000–2011 period. In particular, the data on prices of goods and services as well as the data on regional average monthly wages comes from the Local Data Bank. The data on expenditure comes from the Household Budget Survey. All data are expressed in Polish zloty.

It should be mentioned that the data on prices covers the information about prices of food and nonalcoholic beverages, alcoholic beverages and tobacco, clothing and footwear, housing, water, electricity, gas and other fuels, furnishing household equipment and routine maintenance of the house, health, transport, recreation and culture, and miscellaneous goods and services. Hence, we do not have a data on education or communication services although here one could expect relatively low level of regional disparities in price indices. More problematic is a lack of data concerning housing prices—the data within this category does not include information about land price or renting. This may considerably reduce overall value of price indices for regions with big agglomeration such as Warsaw or Katowice.

16.4 Empirical Results

The PPP deflators estimated in accordance with the Eurostat/OECD methodology confirm the existence of substantial price differentials between Polish regions. Maps 16.1 and 16.2 show the spatial distribution of PPP deflators in 2000 and 2011. It is easy to find that in 2000, the highest level of price indices was observed in the capital region (mazowieckie) and three regions placed in the north-western part of the country (lubuskie, pomorskie, and zachodniopomorskie). On the other hand, the lowest level of prices was found in the central and eastern part of Poland (with the lowest values of the PPP deflators in kujawsko-pomorskie and podkarpackie).

These results are definitely not in line with the theoretical previsions of the New Economic Geography models. First, the region with the highest level of economic activity (mazowieckie) does not have the lowest price index. Second, peripheral regions neither have the highest price indexes. The remarkable exceptions are the three north-western regions. Still, in the case of lubuskie and zachodniopomorskie,



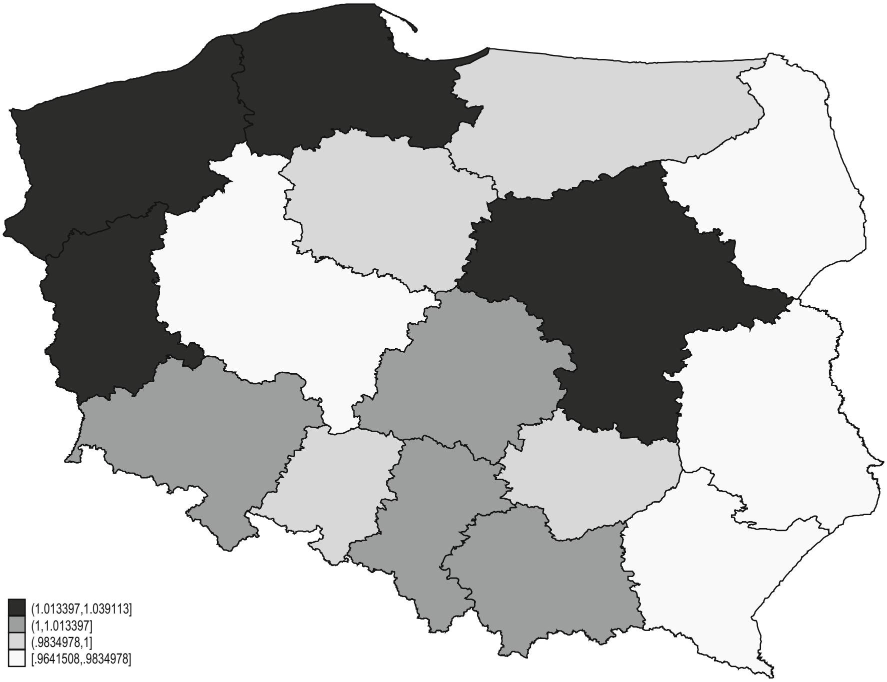
Map 16.1 Regional differentials in prices in 2000

one may try to explain the high level of prices by blaming Germans who come for shopping from their eastern border regions (this argument hardly applies to pomorskie voivoship though).

Once we compare the distribution of price differentials in 2000 and 2011, we notice immediately that there have been very few changes during this period. Probably the most important is significant increase of price index in łódzkie and at the same time, a decrease of overall level of prices in lubelskie. The main pattern of spatial distribution of price disparities in 2011 remains the same as in 2000.

We may ask ourselves though to what extent high regional price indices are correlated with high nominal wages, as suggested in other papers (e.g., Tabuchi 2001). Here, the correlation coefficient equals 0.5795 and is statistically significant at the 5 % level for the 2011 data. It drops, however, to 0.2736 only once we consider the data for the entire 2000–2011 period. In this sense, we may say that in Polish case, there exists a weak correlation only, at least at the NUTS2 level regions.

The above result can be at least partially explained by the existence of the border effect. If we take a look at the spatial distribution of nominal wages (see Map 16.3), we find that western border regions with high level of price indices do not necessarily have high level of nominal wages. Also the price indices of eastern regions do not seem to be highly correlated with nominal wages. Hence,



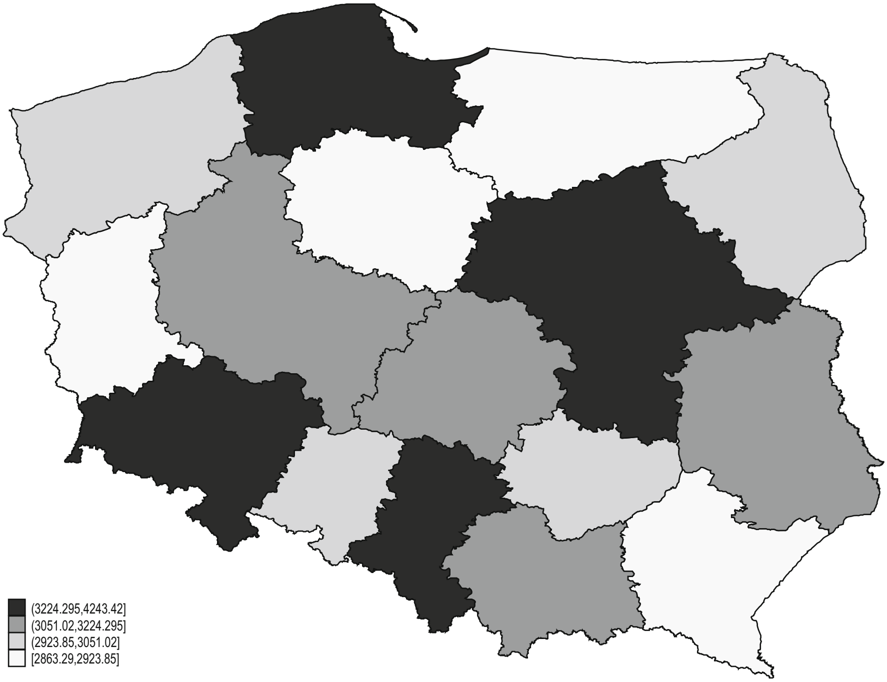
Map 16.2 Regional differentials in prices in 2011

our argument concerning the impact of the western border on regional price indices in these areas seems to be reasonable.[5] On the other hand, high level of nominal wages may at least partly explain high price index observed previously in pomorskie voivodship.

The results of simple regression analysis provide formal verification of the impact of the borders on regional price indices (see Table 16.1). Here, the dummy variable for regions at the western Polish border is positively correlated with the regional level of price index between 2000 and 2011. So on average, price indices of regions situated at the western border are more than 3 % higher than the indices of the remaining regions. Exactly opposite situation is observed at the eastern border, where the dummy variable is negatively correlated with price index. Here, price indices are on average 2 % lower than in other parts of Poland.

The robustness of the results is proven since the coefficients hardly change once we add time and regional dummies (Model 2 and Model 3). We also confirm the positive relation between nominal wages and regional prices in the analyzed period. The coefficient of the nominal wages increases substantially once we add year and

[5]Similar argument can be used for explaining low level of price indices in regions placed at the eastern border of Poland.

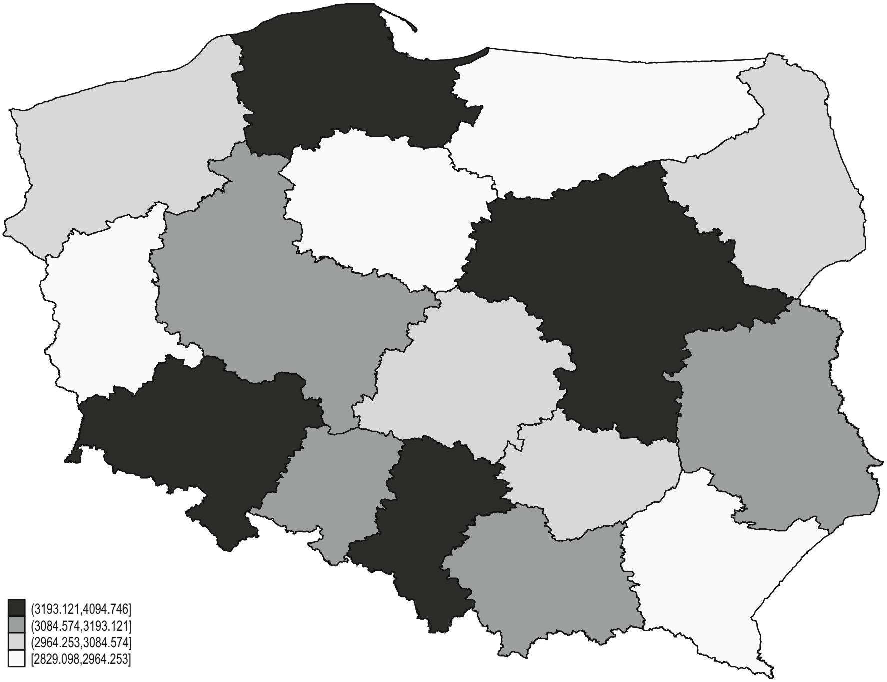


Map 16.3 Spatial distribution of nominal wages in 2011

Table 16.1 The impact of the border effect on regional price indices (dependent variable – price index)

	(1)	(2)	(3)
Variables	Model	Model	Model
Nominal wages	0.028***	0.129***	0.126***
	(0.006)	(0.008)	(0.045)
German border	0.031***	0.038***	0.031***
	(0.003)	(0.002)	(0.004)
Eastern border	−0.022***	−0.014***	−0.016***
	(0.003)	(0.002)	(0.006)
Constant	0.787***	0.029	0.056
	(0.045)	(0.061)	(0.343)
Time dummies	No	Yes	Yes
Region dummies	No	No	Yes
Observations	192	192	192
R-squared	0.48	0.68	0.92
Adj. R-squared	0.47	0.66	0.91

OLS estimation, robust standard errors in parentheses, ***$p < 0.01$



Map 16.4 Spatial distribution of real wages in 2011

region dummies. Still, there is hardly a difference between the results of Model 2 and Model 3.

The question is now whether the application of regional PPP deflators may significantly influence the results of our analysis. Here, the first impression may be that not really, since the spatial distribution of real wages in 2011 does not differ much from the distribution of nominal wages. The only noteworthy exception is a relative deterioration of wage level in łódzkie and improvement in opolskie voivodship (see Map 16.4).

Once we look at the numbers, real wages are relatively lower (as compared to the national average) in the most developed areas (dolnośląskie, mazowieckie,and śląskie) and higher in the lagging behind ones (lubelskie, podkarpackie, podlaskie, świętokrzyskie i warmińsko-mazurskie). As an illustration, in Table 16.2, we show the data concerning regional wages in 2011 before and after using the PPP deflators. Here we find that wages in the richest mazowieckie voivodship, as compared to the national average, decrease by more than 4 percentage points after applying regional PPP deflators. On the other hand, relative wage level in the poorest regions increases up to 3 percentage points (lubelskie).

Table 16.2 Regional wages in 2011 at the NUTS2 level in Poland—the impact of the PPP deflators

Region	Nominal wage	Nominal wage Poland = 100	Real wage	Real wage Poland = 100
Dolnośląskie	3,374.45	99.15	3,339.27	98.11
Kujawsko-pomorskie	2,906.32	85.39	2,923.88	85.91
Lubelskie	3,066.32	90.09	3,180.33	93.44
Lubuskie	2,903.70	85.31	2,829.09	83.12
Łódzkie	3,053.22	89.71	3,044.94	89.46
Małopolskie	3,134.06	92.08	3,122.59	91.75
Mazowieckie	4,243.41	124.68	4,094.74	120.31
Opolskie	3,048.82	89.58	3,086.5	90.69
Podkarpackie	2,887.87	84.85	2,953.84	86.79
Podlaskie	3,002.37	88.21	3,082.61	90.57
Pomorskie	3,314.53	97.39	3,205.90	94.19
Śląskie	3,553.67	104.41	3,506.70	103.03
Świętokrzyskie	2,941.38	86.42	2,986.70	87.75
Warmińsko-mazurskie	2,863.29	84.13	2,896.21	85.10
Wielkopolskie	3,101.33	91.12	3,153.36	92.65
Zachodniopomorskie	3,040.79	89.34	2,974.65	87.40
Polska	3,403.51	100.00	3,403.51	100.00

Source: Author's preparation

The above results suggest that we should observe a reduction in dispersion of regional wages[6] once we refer to the real instead of nominal ones. Indeed, in the case of the 2010 data, sigma convergence falls from 0.127, calculated for nominal wages, to 0.119, computed using the data adjusted for regional prices. The introduction of the PPP deflators has also an impact on the results of the standard convergence analysis (see Table 16.3). Once we make a panel OLS regression for beta convergence, we find that there is no absolute convergence between 2000 and 2011 neither in the case of nominal wages nor in the case of real ones (models 1 and 2). The latter stays clearly in opposition to the real wage equalization process suggested by Krugman and Livas Elizondo (1996) and assumed also in other New Economic Geography models. Still, the value of coefficient for log of real wages is higher and its significance almost doubles the one for nominal ones. This may suggest that there are some significant differences in the evolution of either of them. It is noteworthy that in both cases, we confirm the existence of conditional beta convergence (models 3 and 4).

The differences in the evolution of regional disparities in nominal and real wages can be proved once we examine the evolution of sigma convergence (see Fig. 16.1).

[6]So-called sigma convergence, expressed as $\sigma = \left[\sum_{i=1}^{16}\left(\log w_i - \overline{\log w}\right)^2/16\right]^{1/2}$.

Table 16.3 The results of the standard convergence analysis

Variables	(1) Model	(2) Model	(3) Model	(4) Model
Log nominal wages	−0.007		−0.357***	
	(0.007)		(0.055)	
Log real wages		−0.012		−0.368***
		(0.009)		(0.060)
Constant	0.125**	0.161**	2.771***	2.849***
	(0.055)	(0.066)	(0.417)	(0.454)
Time dummies	Yes	Yes	Yes	Yes
Region dummies	No	No	Yes	Yes
Observations	176	176	176	176
R-squared	0.83	0.80	0.87	0.85
Adj. R-squared	0.81	0.79	0.85	0.82

OLS estimation, standard errors in parentheses, $^{***}p < 0.01$, $^{**}p < 0.05$

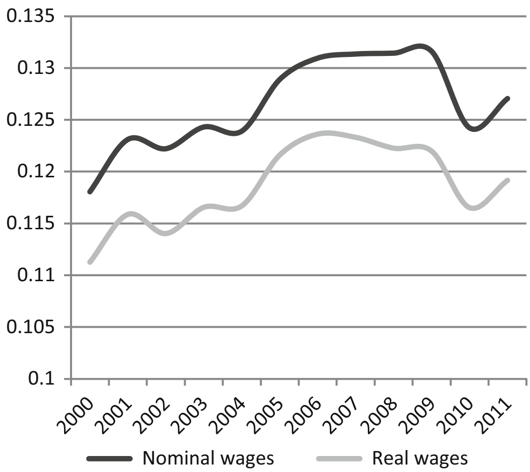


Fig 16.1 Regional wages sigma convergence among Polish NUTS2 regions between 2000 and 2011—the impact of the PPP deflators

Even though it looks pretty similar in the first half of the analyzed period, there are symptoms of divergence between the two lines between 2006 and 2009. As a matter of fact, during this time interval, we observe increasing dispersion of nominal wages and decreasing dispersion of real wages. Here, we may speculate whether this is just a deviation from the long-term trend or rather a beginning of the new one.

One may wonder whether the changes caused by the inclusion of the PPP deflators can be really considered as significant ones. Especially, since the analysis of beta convergence do not show an important impact on the evolution of regional income disparities over time. Here, we believe that the application of PPP deflators to the analysis of regional wage disparities may, in fact, lead to reach new conclusions. The good example is a simple analysis of sigma convergence evolution discussed above. Moreover, we should take into account the possible consequences of application of the PPP deflators computed for lower level of territorial units. In the case of Poland, NUTS2 regions are rather big and display a high level of internal heterogeneity. Hence, it is very likely that once we were able to calculate real wages for NUTS3 regions, their evolution would be much more different from the evolution of nominal ones.

16.5 Conclusions

In this chapter, we discussed the results of application of regional PPP deflators in Poland at the NUTS2 level, in terms of their impact on the analysis of regional wage differentials. Here, Poland is one of the very few EU Member States where the statistical office collects all the necessary data. We also verified empirically theoretical previsions of the New Economic Geography models, concerning the level of regional price indices of the core and peripheral areas.

Contrary to the assumptions of the New Economic Geography models, the highest level of price indices was observed in two regions with high nominal wages and other two bordering Germany. At the same time, the lowest level of prices was found in the central and eastern parts of Poland. As suggested in other empirical studies, we find rather high correlation between regional price indices and nominal wages. Notwithstanding, this is not relevant in the case of the western border regions, where high level of price indices is not accompanied by high level of nominal wages.

The introduction of regional PPP deflators leads to a decrease of regional wage dispersion at the NUTS2 level, expressed by the sigma convergence (as compared to the dispersion of nominal wages). Yet, our results show that there is no convergence of real wages between 2000 and 2011 and again confirm that certain theoretical assumptions of the New Economic Geography framework may be inadequate. Moreover, although generally the evolution of regional wage disparities does not seem to be greatly altered by the application of the PPP deflators, a closer look at the evolution of sigma convergence suggests that there are some significant differences. In particular, we find that between 2006 and 2009, there was an increasing dispersion of nominal wages and a decreasing dispersion of real wages. We believe that the computation of PPP deflators at lower level of territorial units may, in fact, lead to even more interesting results.

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