Chapter 12
Productivity Gaps Among European Regions

Claudio Cozza, Raquel Ortega-Argilés, Mariacristina Piva, and Rui Baptista

Abstract How is the R&D-productivity link affected by the environment where firms locate? Are companies located with their registered offices in more R&D favorable environments better able to translate their R&D knowledge into productivity gains? Our paper tries to answer these questions analyzing - in the European context - if R&D performing companies cluster themselves in “higher-order R&D regions”, as the Economic Geography theories postulate, inducing a polarisation in terms of labour productivity in comparison with firms located in “lower-order R&D regions”.

The proposed microeconometric estimates are based on a unique longitudinal database of publicly-traded companies belonging to manufacturing and service sectors. The final unbalanced sample comprises 626 European companies for a total of 3,431observations, covering the period 1990-2008. Results show that European “higher-order R&D regions” not only invest more in R&D, but also achieve more in terms of productivity gains from their own research activities. Results also show that in the case of “lower-order R&D regions”, physical capital stock is still playing a dominant role.

C. Cozza (✉)
FORMIT Fondazione per la Ricerca sulla Migrazione e Integrazione delle Tecnologie,
Via G.S. Roccatagliata 4, Rome 00152, Italy
e-mail: claudio.cozza@me.com

R. Ortega-Argilés
Faculty of Economics and Business, Department of Global Economics
and Management and Department of Economic Geography, University of Groningen,
PO Box 800, Groningen, 9700AV, The Netherlands
e-mail: r.ortega.argiles@rug.nl

M. Piva
Dipartimento di Scienze Economiche e Sociali, Università Cattolica del Sacro Cuore,
Via Emilia Parmense, 84, Piacenza, 29122, Italy
e-mail: mariacristina.piva@unicatt.it

R. Baptista
DEG, Instituto Superior Técnico, Av. Rovisco Pais, Lisbon, 1049-00, Portugal
e-mail: rui.baptista@ist.utl.pt

D.B. Audretsch et al. (eds.), *Technology Transfer in a Global Economy*,
International Studies in Entrepreneurship 28, DOI 10.1007/978-1-4614-6102-9_12,

1 Introduction

This volume on "Technology Transfer in a Global Economy" following a conference on the topic puts together contributions from different business and economics literature strands. Global technology transfer was empirically analysed using different quantitative and qualitative techniques; among other topics the conference presented works based on the link between academy and industrial research; technological growth "external" to the firm, cooperation or technology acquisitions; and sectoral and product value chains.

The volume stresses the important aspect of the geographical level – national or regional – in conducting analysis of the global context. Although we live in a global economy, where technological links have to be analysed on the whole world scenario, the national and subnational patterns still help in explaining the global tendency. Even more than before, the subnational analysis constitutes the building brick to understand how world balances are changing.

This chapter addresses all these issues through a quantitative analysis of the link between R&D and productivity at the regional level. The global economic tendency is analysed looking at the behaviour of the global R&D business performers. The hypothesis on regional technology transfer focuses on how companies located in a favourable environment for R&D can better translate their knowledge capital into productivity gains. For the location, NUTS 1 level classification has been adopted. Additionally, the analyses have taken into consideration the importance of the sectoral belonging, with regard to industrial sectoral breakdown (manufacturing versus services) and the technological intensity of the sector (high-, medium- and low-tech sectors).

Previously applied literature shows that the economic performance of regions (proxied by GDP, GDP per capita or labour productivity) has a higher variability than the one of countries.[1] Indeed, differences in the performance across regions within the same country are often greater than differences between countries (OECD 2009a, b). The main reason is that "localised" factors seem to play a greater role than national factors in determining the performance of regions. Each region is endowed with very different production structure, comparative advantages, location and geographic characteristics, institutions, policies and assets. In Europe, indeed, regions appear to be extremely heterogeneous.

The inequalities between regions are often an outcome of different processes. One of the most significant is the geographical concentration of economic activity. The concentration of economic activity is characterised by the presence, activity and interactions of private and public actors (firms, training institutions, trade unions, universities, public research centres) that chose the region to locate and operate. The peculiarities characterising each region (such as different supply factors) have a direct effect on firms' decisions to locate and, subsequently, might determine firms' performance and growth. In principle, growth opportunities exist

[1] In this publication, region is used to mean a subunit within a country, rather a supranational grouping of countries.

in all regions, but firms tend to locate in regions that might offer a favourable environment to pursue their production and growth targets. This chapter is focused on how companies located with their registered offices in a favourable environment for R&D can better translate their knowledge capital into productivity gains.

Recent empirical works have shown how the endogenous growth can be applied to the regional level, underlining the crucial role of knowledge stock (R&D or patents) and human capital (skilled labour) in explaining the differences in productivity across regions (Gumbau-Albert and Maudos 2006; Dettori et al. 2008; Fischer et al. 2008; Bronzini and Piselli 2009). We analyse this hypothesis for the European case splitting our sample between the so-called higher-order R&D regions and lower-order R&D regions. We want to test if following the localisation logic, R&D-performing companies cluster themselves in "higher-order regions" and get better labour productivity performance in comparison with firms located in "lower-order regions" (Cantwell and Iammarino 2001).

In order to run this exercise, we use firm-level data. The data sample covers the period 1990–2008, depending on the number of years available in each company's history; therefore, the sample used is unbalanced in nature and comprises 626 European companies for a total of 3,431 observations.[2]

Results show that regions investing more in R&D are also characterised by a better ability to translate the R&D investment in an increase in labour productivity both in manufacturing and service sectors. On the other side, results show that in the case of lower-order R&D regions, the physical capital stock is still playing a dominant role.

After this Introduction, the rest of the chapter is organised as follows: Sect. 2 provides a survey of the theories and previous empirical literature on the tendency of firms to agglomerate and polarise in regions and on the different effects that input factors have on firm productivity; in Sect. 3, data, variable construction and methodological issues are discussed; Sect. 4 deals with the empirical results, and finally, Sect. 5 addresses the main conclusions of the work and some policy implications derived from the analysis.

2 Literature Review

2.1 Economic Geography Theories: The Role of Geography

As we indicated in the introduction, firms locate in regions where they might be able to obtain better results from the inputs used for their production process. One of the

[2] In case of multilocated or multinational corporations, data refer to global activities controlled by mother companies from the region of their registered office. In the estimates, therefore, the NUTS (Nomenclature of Territorial Units for Statistics) codes always refer to the regions from where company activities on the whole are owned and controlled.

main issues in this chapter is focused in analysing if the effects on productivity of different production inputs can differ among firms located in different environments. We can illustrate this idea by some concepts from economic geography theories.

Firm creation, performance and growth depend on the conditions of both the environment and the market where firms operate (see the pioneer works: Krugman 1991; Porter 1990, 1998, 2000). The creation of agglomeration patterns in economic activity is centred in various concepts: localisation economies (cluster creation), input–output linkages and technological spillovers.

Localisation economies turn out to be relevant when many firms operating in the same industry locate close to each other. Sources of localisation economies can differ among different industries. In general, the main important sources that can facilitate and encourage the proximity of firms are as follows: benefits from accessing to a pool of labour with the required skilled and abilities, increasing returns to scale in intermediate inputs and relative ease of communication and circulation of innovative ideas. As more firms in same and/or *related industries* (Frenken et al. 2007) cluster together, cost of production may decline significantly.

Input–output linkages are crucial in the creation of agglomeration economies. The accumulation of certain input factors (knowledge, natural, labour resources) in certain locations creates a favourable industrial environment capable to enhance the economic growth by the means of the development of specific industries (Krugman and Venables 1996). Following this line of reasoning, we can say that economic activity will tend, accordingly to their needs, to agglomerate in certain areas producing *regional (and national) specialisation production patterns*.

The positive effect of the accumulation of skills, know-how and knowledge in certain locations in explaining the *creation of clusters* started with the work of Marshall (1890), and the idea has evolved by other authors like Malmberg and Maskell (1997, 2002) or Maskell (2001). Evolutionary economics theories that focus the attention in the historical evolution of the localisation processes of firms introduce other concepts like *industrial relatedness*, *organisational ecology* or *industrial heritage*. The presence of related industries has increased importance where local access to specialised skilled labour force is determinant or knowledge sharing between the actors (Frenken et al. 2007) in firm heritage processes (Klepper 2007) and organisational ecology framework (among others, Hannan et al. 1995; Carroll and Hannan 2000; Audia et al. 2006).

Furthermore, this accumulation effect is conditional on the *absorptive capacity* of firms. As Cohen and Levinthal (1990) have argued, firms can understand, absorb and implement external knowledge only when it is close to their own knowledge base. The potential learning mechanism might be at work horizontally that is from spillovers from other producers and competitors, or vertically, by interacting with upstream suppliers and downstream users, as well as from independent research carried out in the regional, national or international science and technology networks by universities and research institutes. Boshma and Frenken (2009) show that knowledge accumulation tends to operate at the regional level because the mechanisms through which they operate (like spinoff activity, firm diversification, labour mobility or social networking) tend to have a regional bias.

Finally, *technological spillovers* are another source of localisation economies. Technical knowledge and expertise, knowledge spillovers, technological learning, higher R&D returns and other important synergies for the innovation process (von Hippe 1988; Feldman 1994; Baldwin and Forslid 2000; Martin and Ottaviano 2001; Forslid and Wooton 2003; Antonelli 2010) are particularly relevant in a regional framework. In this perspective, the significance of the regional dimension of innovation systems has emerged as the logical consequence of the interactive model (Kline and Rosenberg 1986), which indeed puts the emphasis on the relations with knowledge sources external to the firm. Such relationships – at interfirm level, between firms and the science infrastructure, between the business sector and the institutional environment, etc. – are strongly influenced by spatial proximity mechanisms that favour processes of polarisation and cumulativeness (see, e.g. Lundvall 1988; von Hippe 1988; Cooke et al. 1997).

The theoretical literature explored in the previous part suggests that there are benefits for the firm adopting inputs available in the geographical area where it is located. This could, in turn, be translated into an increase in its performance. However, when the inputs are R&D investments, the cumulative efforts may widely vary across the different environments. Indeed, technological opportunities and appropriability conditions are so different across regions depending on the level of knowledge found in the region and the sectoral composition.

In a sense, the endogenous growth approach (Romer 1986, 1987, 1990; Lucas 1988; Aghion and Howitt 1992)[3] applied at the regional level reflect the crucial role of knowledge stock (proxied by either R&D or patents) and human capital in explaining the differences in performance across regions, such as total factor productivity (see, for instance, Dettori et al. 2008, studying 199 European regions over the period 1985–2006; Fischer et al. 2008, analysing 203 European regions over the period 1997–2002; Gumbau-Albert and Maudos 2006, investigating 17 Spanish regions over the period 1986–96; Bronzini and Piselli 2009, studying 19 Italian regions over the period 1985–2001).

Furthermore, this result might come from the agglomeration patterns creating economies of scale and scope that have a direct influence in the performance and growth of companies located in certain regions. Cantwell and Iammarino's work (1998, 2000, 2001) is centred in the presence of large, mainly of them multinational or global, players, in determining the specialisation patterns of certain regions by the location of their sites. Their works show that the patterns of large players create endogenous patterns to attract other innovative actors in order to create lines of specialisation through intra-firm networks. Their studies show that geographical

[3] Romer (1986) and Lucas (1988) defined a model where the main premises where knowledge was considered an input of production and displayed increasing marginal productivity, increasing returns to scale and decreasing returns in production of new knowledge. Lately, Romer (1987, 1990) and Aghion and Howitt (1992) models introduced the assumption of imperfect competition and the fact that technological change aroused by the international decisions from profit-maximising agents. R&D activities reward firms through monopolistic power, and their effect is higher in environments where competition is higher (in specialised clusters of high-tech firms, higher-order R&D regions in our work).

concentration of large company innovation activity is quite pronounced in most European countries.

Le Bas and Sierra (2002) study the question of the determinants of the foreign location of technological activities of multinational firms. They explore if multinationals locate their knowledge activities as a consequence of their home country advantages or according to host country strengths. The study is based on a panel of 345 multinationals with the greatest patenting activity in Europe. They found that the strategies of multinationals differ among countries of origin and countries of destination. Finally, their results confirm the work by Patel and Vega (1999) based on a sample of 220 high-patenting multinationals. Both works show that more than 70% of the multinationals locate their activities in technological activities where they are already strong at their home country.[4]

Moreover, Iammarino and McCann (2010) provide an explanation for why the strategies of multinational enterprises result in a pattern of "concentrated dispersion" worldwide. They claim that firms' accumulated different competences in time and space have an impact on their incentives to co-locate and tap into complementary knowledge bases in different locations. This shows how single important player might drive and determine sectoral geographical specialisation and innovative strategies.

2.2 The Role of R&D to Enhance Firm Productivity: Firm and Sectoral Evidence

Since Zvi Griliches' (1979) work, the literature devoted to investigate the role of R&D on productivity at the firm and sectoral level has found robust evidence of a positive and significant impact of knowledge capital on firm productivity.

In general, microeconometric literature indicates a significant and positive role of R&D in enhancing productivity at the firm level independently of the proxy for productivity used (labour productivity as the ratio between value added and employment or the ratio between value added and hours worked, total factor productivity, Solow's residual, etc.). Furthermore, sectoral studies clearly suggest a greater positive impact of R&D efforts on firm productivity in high-tech sectors rather than in low-tech ones.

Examples are Griliches and Mairesse (1982) and Cuneo and Mairesse (1983), who performed two companion studies using micro-level data and making a distinction between firms belonging to science-related sectors and firms belonging to other sectors. They found that the impact of R&D on productivity for scientific firms (elasticity equal to 0.20) was significantly greater than for other firms (0.10).

By the same token, Verspagen (1995) tested the impact of R&D expenditures using OECD sectoral-level data on value added, employment, capital expenditures

[4] Defined as the technological fields in which a particular country exhibits a specialisation index greater than unity.

and R&D in a standard production function framework. The author singled out three macro sectors: high-tech, medium-tech and low-tech, according to the OECD classification (Hatzichronoglou 1997). The major finding of his study was that the impact of R&D was significant and positive only in high-tech sectors, while for medium and low-tech sectors, no significant effects could be found.

Using the methodology set up by Hall and Mairesse (1995), Harhoff (1998) studied the R&D/productivity link – using a slightly unbalanced panel of 443 German manufacturing firms over the period 1977–1989 – and found a significant impact ranging from a minimum of 0.068 to a maximum of 0.137, accordingly to the different specifications and the different econometric estimators adopted. Interestingly, the effect of R&D capital was considerably higher for high-technology firms rather than for the residual groups of enterprises. In particular, for the high-tech firms, the R&D elasticity always turned out to be highly significant and ranging from 0.125 to 0.176, while for the remaining firms, the R&D elasticity resulted either not significant (although positive) or lower (ranging from 0.090 to 0.096), according to the different estimation techniques.

More recently, Wakelin (2001) applied a Cobb–Douglas production function where productivity was regressed on R&D expenditures, capital and labour using panel data (170 UK quoted firms during the period 1988–1992). She found that R&D expenditures had a positive and significant role in influencing a firm's productivity growth; however, in firms belonging to sectors defined as "net users of innovations", R&D activities turned out to have a significantly larger impact on productivity.

Rincon and Vecchi (2003) also used a Cobb–Douglas framework in dealing with panel microdata extracted from the Compustat database over the time period 1991–2001. R&D-reporting firms appear to be more productive than their non-R&D-reporting counterparts throughout the entire time period. Sectoral macroeconomic disparities in the R&D productivity link were found in their analysis; the positive impact of R&D expenditures turned out to be statistically significant both in manufacturing and services in the USA, while in the three main European countries (Germany, France and the UK), only a positive effect was found only in manufacturing. Their estimated significant elasticities ranged from 0.15 to 0.20.

Kwon and Inui (2003) analysed 3,830 Japanese firms with no less than 50 employees in the manufacturing sector over the period 1995–1998, also using the methodology set up by Hall and Mairesse (1995). Using three different estimation techniques (within estimates, first difference and 3-year differences), they found a significant impact of R&D on labour productivity, with high-tech firms systematically showing higher and more significant coefficients than medium- and low-tech firms.

Ortega-Argilés et al. (2011) have looked at the top EU R&D investors, using an unbalanced longitudinal database consisting of 577 large European companies over the period 2000–2005, extracted from the UK-DTI Scoreboards. The authors found that the R&D productivity coefficient was significantly different across sectors. In particular, the coefficient increased monotonically moving from the low-tech to the medium-high and high-tech sectors, ranging from a minimum of 0.03/0.05 to a maximum of 0.14/0.17. This outcome has been interpreted as evidence that firms in high-tech sectors are still far ahead in terms of the impact on productivity of their R&D investments, at least as regards top European R&D investors.

With the aim of addressing some conclusions of the comparison of the effect of different types of R&D/innovations on firm productivity between manufacturing and knowledge-intensive services (KIS) companies in the Spanish region of Catalonia, Segarra (2010), using a sample extracted from the CIS4 (2002–2004), concludes that a considerable heterogeneity in firm performances can be found in the comparison of manufacturing and service industries and between high- and low-tech manufacturing firms; results show that especially KIS sectors play a key role in Catalonian economy.

On the whole, previous firm and sectoral empirical studies – using different data sets across different countries – seem to suggest a greater impact of knowledge and R&D investments on firm productivity in the high-tech sectors rather than in the low-tech ones.

3 Data and Method

3.1 The Data

The microdata used in this study were provided by the JRC-IPTS (Joint Research Centre, Institute for Prospective Technological Studies) of the European Commission; the information provided only concerns publicly traded companies and is extracted from a variety of sources, including companies' annual reports, Securities and Exchange Commission (SEC) 10-K and 10-Q reports, daily news services and direct company contacts, using standardised data definitions and collection procedures to assure consistent presentation of data.[5]

Available data includes:

- Company identification, name and address and industry sector (Global Industry Classification Standard (GICS) that can be translated in the standard SIC classification)
- Fundamental financial data including income statements, cash flows, taxes, dividends and earnings, pension funds, property assets and ownership data
- Fundamental economic data, including the crucial information for this study, namely, sales, cost of goods (the difference between the former and the latter allows us to obtain value added), capital formation, R&D expenditures and employment

Given the crucial role assumed by the R&D variable in this study, it is worthwhile to discuss in detail what is intended by R&D in our database. This item represents

[5] The original data source being Compustat Global data set provided by Standard & Poor's, for additional information about the data source, consult: http://be.ncue.edu.tw/compustat/manual/MK-CGDC4-02.pdf.

all costs incurred during the year that relate to the development of new products and services. It is important to notice that this amount is only the company's contribution and excludes amortisation and depreciation of previous investments, so being a genuine flow of current in-house R&D expenditure.[6] On the whole, the adopted definition of R&D is quite restrictive and refers to the genuine flow of current additional resources coming from internal sources and is devoted to the launch and development of entirely new products.

The period covered is 1990–2008; however, the number of years available for each company depends upon the company's history; therefore, the data source is unbalanced in nature and comprises 626 firms for a total of 3,431 observations.

Once we acquired the rough original data from IPTS, we proceeded in the construction of a longitudinal database that would be adequate to run panel estimations for testing the hypotheses discussed in the previous section.

3.2 Construction of the Data Set

The first step was focused on the data extraction. In guiding the extraction of the data from what provided, the following criteria were adopted:

– Selecting only those companies with R&D > 0 in, at least, 1 year of the available time span.
– Selecting only those companies located in the EU 27 countries.
– Extracting information concerning R&D, sales, cost of goods (the difference between sales and cost of goods allowed to obtain value added), capital formation, R&D expenditures and employment. More specifically, this is the list of the available information for each firm included in the obtained workable data set: country of incorporation (location of the headquarter), industry code at 2008, R&D expenses, capital expenditures, net turnover, cost of goods sold and employees.
– All the value data were expressed in the current national currency in millions (for instance, countries which are currently adopting euro have values in euro for the entire examined period).

The second step focused on the deflation of current nominal values. Nominal values were translated into constant price values through GDP deflators (source: IMF) centred in year 2000. For a tiny minority of firms reporting in currencies different from the national ones (viz. 41 British firms, 9 Dutch firms, 4 Irish firms, 2 Luxembourg firms, 1 German and 1 Swedish firms reporting in US dollars and 7 British firms, 2 Danish firms and 1 Estonian firm reporting in euro), we opted for deflating the nominal values through the national GDP deflator, as well.

[6] In particular, the figure excludes the following: customer- or government-sponsored R&D expenditures engineering expenses such as routinised ongoing engineering efforts to define, enrich or improve the qualities and characteristics of the existing products, inventory royalties, market research and testing.

Once we obtained constant 2000 price values, as a third step, all figures were converted into US dollars using the PPP exchange rate at year 2000 (source: OECD).[7] The fourth step was devoted to give format to the data string. The obtained unbalanced database comprises 926 companies, 2 codes (country and sector) and 5 variables (see the bullet points above) over a period of 19 years (1990–2008).

Since one of the purposes of this study is also to distinguish between high-tech and medium/low-tech sectors, a third code was added, labelling as high-tech the following sectors[8]:

- SIC 283: Drugs (ISIC Rev.3, 2423: Pharmaceuticals)
- SIC 357: Computer and office equipment (ISIC Rev.3, 30: Office, accounting and computing machinery)
- SIC 36 (excluding 366): Electronic and other electrical equipment and components, except computer equipment (ISIC Rev.3, 31: Electrical machinery and apparatus)
- SIC 366: Communication equipment (ISIC Rev.3, 32: Radio, TV and communications equipment)
- SIC 372–376: Aircraft and spacecraft (ISIC Rev.3, 353: Aircraft and spacecraft)
- SIC 38: Measuring, analysing and controlling instruments (ISIC Rev. 3, 33: Medical, precision and optical instruments)

As a fifth step, the following computation of the R&D and capital stocks was used. Consistent with the reference literature (see Sect. 2), the methodology adopted in this study requires us to compute the R&D and capital stocks, accordingly with the *perpetual inventory method*. In practice, the following two formulas have to be applied:

$$K_{t0} = \frac{R\&D_{t0}}{(g+\delta)} \text{ and } K_t = K_{t-1} \cdot (1-\delta) + R\&D_t \tag{12.1}$$

where R&D = R&D expenditures

[7] This procedure is consistent with what suggested by the Frascati Manual (OECD 2002) in order to correctly adjust R&D expenditures for differences in price levels over time (i.e. intertemporal differences asking for deflation) and among countries (i.e. interspatial differences asking for a PPP equivalent). In particular, "…the Manual recommends the use of the implicit gross domestic product (GDP) deflator and GDP-PPP (purchasing power parity for GDP), which provide an approximate measure of the average real "opportunity cost" of carrying out the R&D" (ibidem, p. 217). More in detail, nine companies from four countries (Lithuania, Latvia, Malta and Romania) were excluded, due to the unavailability of PPP exchange rates from the OECD. The ten companies reporting in euro but located in non-euro countries (Denmark, Estonia and the UK) were excluded as well, while the 58 companies reporting in US dollars were kept as such.

[8] The standard OECD classification was taken (see Hatzichronoglou 1997) and extended it including the entire electrical and electronic sector 36 (considered as a medium-high-tech sector by the OECD). We opted for this extension taking into account that we just compare the high-tech sectors with all the other ones and that we need an adequate number of observations within the subgroup of the high-tech sectors.

$$C_{t0} = \frac{I_{t0}}{(g+\delta)} \text{ and } C_t = C_{t-1} \cdot (1-\delta) + I_t \tag{12.2}$$

where I = gross investment
where g is generally computed as the ex ante pre-sample compounded average growth rate of the corresponding flow variable and δ is a depreciation rate.

However, our data set spans 19 years and is unbalanced in nature. This means that only a minority of firms display continuous information all over the entire period, while many firms have information only for one or more spans over the 1990–2008 period and these spans may be either very short or even isolated data. In addition, many firms display left-truncated data.

Given the unbalanced structure of the data set, to strictly apply the Formulas 12.1 and 12.2 for computing initial stocks (using – say – the first 3 years to obtain the ex ante growth rates) would have implied the loss of huge amount of information. In the best case – say a firm with a complete set of 19 data over the period – this methodology would have implied the loss of 3 observations out of 19; in the worst case – say a firm characterised by data available only for some spells of 3 years each – this computation would have implied the loss of all the available information for that particular firm.

In order to avoid this severe loss of available data, we adopted the following criteria. First, it was decided to compute a rate of growth using the initial 3 years of a given spell and then apply it to the initial flow and not to the fourth year (that is our t_0 is the very first year of the spell and so g is an "ex post" 3-year compound growth rate). Second, we iteratively applied this methodology to all the available spans of data comprising at least three consecutive years.[9] The combination of these two choices allowed us to keep all the available information, with the only exceptions of either isolated data or pairs of data.

Although departing from the usual procedure, to rely on ex post growth rates appears acceptable in order to save most of the available information in the data set; however, the impact of this choice on the values assumed by the stocks is limited, since they are also affected by the flow values and the depreciation rates. Finally, the chosen growth rate affects only the initial stock, and its impact quickly smoothes out as far as we move away from the starting year.[10]

[9] This means that for firms characterised by breaks in the data, we computed different initial stocks, one for each available time span, consistent with Hall (2007); however, differently from Hall (2007), we consider the different spans as belonging to the same firm and so we will assign – in the following econometric estimates – a single fixed or random effect to all of the spans belonging to the same company history.

[10] Options for the choice of g – different from the standard one – have been implemented by other authors, as well. For instance, Parisi et al. (2006) assume that the rate of growth in R&D investment at the *firm* level in the years before the first positive observation equals the average growth rate of *industry* of R&D between 1980 and 1991 (the time span antecedent to the longitudinal microdata used in their econometric estimates). In general terms, the choice of a feasible g does not significantly affect the final econometric results of the studies. As clearly stated by Hall and Mairesse (1995, p.270, footnote 9): "In any case, the precise choice of growth rate affects only the initial stock, and declines in importance as time passes".

Therefore – in order to be able to compute R&D and capital stocks according to the procedure described above – only R&D and capital expenditure flows data with at least 3 observations in consecutive years were retained. This implied that 118 companies had to be dropped because they were lacking 3 R&D observations in successive years and 10 additional companies were lacking 3 capital expenditure observations in successive years. Thus, a total of 778 firms were retained at the end of this stage of the cleaning process.

Turning the attention to the depreciation rates (δ), we differentiated both between R&D and capital and between the high-tech sectors and the other sectors, taking into account what is common in the reference literature which assumes $\delta = 6\%$ for computing the capital stock and $\delta = 15\%$ for computing the R&D stock (see Nadiri and Prucha 1996 for the capital stock; Hall and Mairesse 1995 and Hall 2007 for the R&D stock).

Indeed, depreciation rates for the R&D stocks have to be assumed to be higher than the corresponding rates for physical capital, since it is assumed that technological obsolescence is more rapid than the scrapping of physical capital.

However, depreciation rates for the high-tech sectors have to be assumed to be higher than the corresponding rates for medium- and low-tech sectors under the assumption that technological obsolescence – both related to R&D efforts and to the embodied technologies incorporated in physical capital – is faster in high-tech sectors. Specifically, depreciation rates were assumed to be equal to 6% and 7% with regard to physical capital in the low-medium and high-tech sectors, respectively, while the corresponding δ for R&D stocks were assumed equal to 15% and 18%, respectively.

Once computed according to the Formulas (12.1) and (12.2) and the adopted g and δ rates, the resulting stocks were checked and negative ones were dropped.[11] Moreover, we excluded a minority of unreliable data such as those indicating negative sales and cost of goods equal to zero.

After these further removals of data, we ended up with 674 companies, for a total of 3,730 observations.

Finally, the last step was centred in checking for the presence of outliers (i.e. observations that appear to deviate markedly in terms of standard deviations from the relevant mean, possibly implying a bias in the econometric estimates); the Grubbs test (Grubbs 1969) was run on the two critical variables in the analysis: the R&D stock (K) and the physical capital stock (C).

Since the outlier test has to be applied to the variables used in the regression analysis, the test was run on the two normalised stock variables: K/E and C/E (see Eq. 12.3 in Sect. 3.3).

In detail, the Grubbs test – also known as the maximum normed residual test, (Grubbs 1969; Stefansky 1972) – is used to detect outliers in a data set, either creating a new variable or dropping outliers out of the data set. Technically, the Grubbs

[11] The occurrence of negative stocks happens when g turns out to be negative and larger – in absolute value – than δ.

test detects one outlier per iteration[12]: The outlier is expunged from the data set, and the test is iterated until no outliers remain.[13]

After running the Grubbs test, 100 observations turned out to be outliers for the K/E variable and 205 for the C/E variable (6 outliers turned out to be common to both the variables). Therefore, at the end of the process, we ended up with a final data set comprising 626 companies (for a total of 3,431 observations).

3.3 The Econometric Specification and the Regional Subsamples

Consistent with previous literature discussed in Sect. 2, we will test the following augmented production function, obtainable from a standard Cobb–Douglas function in three inputs: physical capital, labour and knowledge capital (see Hall and Mairesse 1995, formulas 12.1, 12.2, 12.3, pp. 268–69)[14]:

$$\ln(VA / E) = \alpha + \beta \ln(K / E) + \gamma \ln(C / E) + \lambda \ln(E) + \varepsilon \qquad (12.3)$$

Our proxy for productivity is labour productivity (value added (VA), over total employment (E); our pivotal impact variables are the R&D stock (K) per employee and the physical capital stock (C) per employee).

As it is common in this type of literature (see Hulten 1990; Jorgenson 1990; Hall and Mairesse 1995; Parisi et al. 2006), stock indicators rather than flows were considered as impact variables; indeed, productivity is affected by the accumulated stocks of capital and R&D expenditures and not only by current or lagged flows.

Moreover, dealing with R&D stocks – rather than flows – has two additional advantages: On the one hand, since stocks incorporate the accumulated R&D investments in the past, the risks of endogeneity are minimised; on the other hand, there is no need to deal with the complex (and often arbitrary) choice of the appropriate lag structure for the R&D regressor.

---

[12] The default number of iterations is 16,000.

[13] The Grubbs test is defined under the null hypothesis (H_0) that there are no outliers in the data set; the test statistic is $G = \frac{\max_{i=1,..,N} \left| Y_i - \bar{Y} \right|}{s}$ with $\bar{Y}$ and s denoting the sample mean and standard deviation, respectively. Therefore, the Grubbs test detects the largest absolute deviation from the sample mean in units of the sample standard deviation. With a two-sided test, the null hypothesis of no outliers is rejected if $G > \frac{(N-1)}{\sqrt{N}} \sqrt{\frac{t^2_{(\alpha/(2N),N-2)}}{N-2+t^2_{(\alpha/(2N),N-2)}}}$ with $t^2_{(\alpha/(2N),N-2)}$ denoting the critical value of the t-distribution with *(N-2)* degrees of freedom and a significance level of $\alpha/(2\ N)$.

[14] As clearly stated and demonstrated in Hall and Mairesse (1995), the direct production function approach to measure returns to R&D capital is preferred on other possible alternative specifications.

In this framework, R&D and physical capital stocks were computed using the *perpetual inventory method,* according to the Formulas 12.1 and 12.2 reported in the previous section.

Finally, taking per capita values permits both standardisation of our data and elimination of possible size effects (see, e.g. Crépon et al. 1998, p.123). In this framework, total employment (E) is a control variable: If λ turns out to be greater than zero, it indicates increasing returns.

All the variables are taken in natural logarithms.

While *K/E* (R&D stock per employee) captures that portion of technological change which is related to the cumulated R&D investment, *C/E* (physical capital stock per employee) is the result of the cumulated investment, implementing different vintages of technologies. So, this variable encompasses the so-called *embodied technological change*, possibly affecting productivity growth (see Sect. 2).

Table 12.1 reports the correlation matrix of the variables included in Eq. 12.1. As can be seen, a preliminary evidence of the expected positive impacts of both K/E and C/E upon VA/E emerges. Moreover, no evidence of possible serious collinearity problems is evident, since the three relevant correlation coefficients turn out to be less than 0.301 in absolute values.

Besides the overall sample, as discussed in the previous sections, one of the purposes of this study is to investigate possible regional peculiarities in the relationship between R&D and productivity. In order to check for specificities, we decided to split the European regions in two defined groups: "higher-order R&D regions" and "lower-order R&D regions". We adopted the NUTS1 geographical classification to split the sample in these two groups independently from the country regions where they belong to.[15] Regions were split according to their R&D intensity level, measured by the R&D/GDP ratio in 2005, as provided by Eurostat. In order to have two comparable subsamples, we assumed an R&D/GDP (R&D measured as BERD – Business Enterprise Research and Development) ratio equal to 1.8% as a feasible threshold, generating an "innovative group" of 328 firms (1,827 observations) versus a "weakly innovative group" of 298 companies (1,604 observations). In the following Table 12.2, we report the ranking of the regions, their R&D/GDP ratios, the number of firms and the number of observations. In bold are the regions belonging to the higher-order R&D regions.

4 Results

Specification (12.3) was estimated through different estimation techniques. Firstly, pooled ordinary least squared (POLS) regressions were run to provide preliminary reference evidence. Although very basic, these POLS regressions were controlled for heteroscedasticity (we used the Eicker/Huber/White sandwich estimator to compute robust standard errors) and for a complete set of three batteries of dummies,

[15] Final sample (number of firms and observations) by country is reported in Table 12.8 in the Appendix.

Table 12.1 Correlation matrix

	Log(value added per employee)	Log(R&D stock per employee)	Log(physical stock per employee)	Log(employment)
Log(value added per employee)	1			
Log(R&D stock per employee)	0.323	1		
Log(physical stock per employee)	0.282	0.126	1	
Log(employment)	−0.030	−0.202	0.301	1

Note: all correlation coefficients are 1% significant

namely, country (18 countries), time (19 years) and sector (52 two-digit SIC sectors) dummies.

Secondly, fixed effect (FE) regressions were performed in order to take into account the firm-specific unobservable characteristics such as managerial capabilities. The advantage of the FE estimates is that different firms are not pooled together but taken into account individually. The disadvantage is that country and sector dummies are dropped for computational reasons, since they are encompassed by the individual dummies. Thirdly, random effect (RE) regressions were run to provide more complete results, where both individual (randomised) effects are taken into account together with the possibility to retain all the entire batteries of dummies.

In Table 12.3, the benchmark European figures are compared with the estimates coming out from the separate estimates for the group of firms located in higher-order or higher innovative regions versus their counterparts located in the lower-order or lower innovative ones. As can be seen, "more is better"; those regions that invest more in R&D are also characterised by a better ability to translate the R&D investment in an increase in productivity. In more detail, all the three R&D coefficients (uniformly significant) are larger in magnitude when estimated within the group of the innovative regions. In other words, firms located in innovative European regions not only invest more in R&D but also achieve more in terms of productivity gains from their own knowledge investments.

As far as the physical capital stock is concerned, the lower-order innovative European regions seem to be characterised by a dominant role of the embodied technological change, which does not turn out to be crucial in the R&D-intensive regions. If we consider the latter results together with the evidence coming out from Tables 12.6 and 12.7, we come out with a picture where R&D-advanced European regions characterised by high-tech sectors rely on R&D expenditure as the main lever to increase productivity, while lagging regions – specialised in the non-high-tech sectors – rely more on the embodied technological change incorporated in capital formation.

In Table 12.3, it is interesting to notice that the results for the same firms located in higher-order regions show no significant effect of the sectoral composition of the sample on productivity. As can be seen in the fact that the global significance test for the sectoral dummies in the higher-order region' results appears not to be significant, an explanation of that could be found in the fact that innovative regions appear to have a more dynamic environment, with a higher diversification of the sectors in

Table 12.2 European NUTS1 R&D intensities (BERD/GDP) (decreasing order)

NUTS	Code	R&D/GDP	Firms	Observations	NUTS	Code	R&D/GDP	Firms	Observations
Baden-Württemberg	**DE1**	**3.40**	**16**	**96**	Thüringen	DEG	0.95	8	51
Eastern	**UKH**	**3.15**	**30**	**188**	Nord Ovest	ITC	0.93	3	13
Södra Sverige	**SE2**	**3.08**	**25**	**122**	Czech Republic	CZ0	0.91	1	4
Östra Sverige	**SE1**	**2.89**	**35**	**248**	Bremen	DE5	0.91	1	3
Manner-Suomi	**FI1**	**2.48**	**41**	**157**	Est	FR4	0.88	1	8
Zuid-Nederland	**NL4**	**2.39**	**5**	**42**	Norra Sverige	SE3	0.85	1	12
Südösterreich	**AT2**	**2.36**	**3**	**9**	Slovenia	SI0	0.84	1	4
Bayern	**DE2**	**2.30**	**41**	**175**	Ireland	IE0	0.82	8	55
Île de France	**FR1**	**2.10**	**44**	**236**	West Midlands	UKG	0.79	9	38
Hessen	**DE7**	**2.09**	**15**	**112**	Oost-Nederland	NL2	0.76	5	25
Berlin	**DE3**	**1.87**	**9**	**50**	Közép-Magyarország	HU1	0.69	2	10
Denmark	**DK0**	**1.80**	**21**	**152**	West-Nederland	NL3	0.62	15	98
South East	**UKJ**	**1.80**	**43**	**240**	Scotland	UKM	0.60	8	58
Centre-Est	FR7	1.71	8	29	Région de Bruxelles-Capitale	BE1	0.54	6	16
Sud-Ouest	FR6	1.68	1	6	Schleswig-Holstein	DEF	0.52	2	12
Ostösterreich	AT1	1.64	7	20	Wales	UKL	0.52	2	10
North West	UKD	1.59	17	100	Northern Ireland	UKN	0.49	1	3

Westösterreich	AT3	1.52	6	22	Nord Est	ITD	0.47	1	3
Niedersachsen	DE9	1.49	7	40	Estonia	EE0	0.42	1	3
Vlaams Gewest	BE2	1.44	11	52	Centro	ITE	0.41	1	3
Région Wallonne	BE3	1.36	3	14	Yorkshire and the Humber	UKE	0.40	15	88
Luxembourg (Grand-Duché)	LU0	1.35	3	9	North East	UKC	0.39	5	27
East Midlands	UKF	1.32	8	51	Saarland	DEC	0.32	2	12
South West	UKK	1.28	17	111	Attiki	GR3	0.29	8	32
Rheinland-Pfalz	DEB	1.22	5	32	Sur	ES6	0.27	1	2
Hamburg	DE6	1.15	7	31	London	UKI	0.26	59	353
Nordrhein-Westfalen	DEA	1.10	26	133	Alföld és Észak	HU3	0.21	1	2
Sachsen	DED	1.07	1	1	Voreia Ellada	GR1	0.08	1	3
Comunidad de Madrid	ES3	1.04	2	5					

Note: R&D/GDP intensities are computed based on 2005 values (due to missing values, for FR1, FR4, FR6, FR7 2004 values were used; for DK0 2007) (Eurostat).

contrast with the situation in lower-order regions where only certain sectors are relevant to explain their labour productivity.

Macroeconomic conditions effects, explained by the significance of the time and country dummy sets, play a role on labour productivity for the firms operating in higher-order regions. All these conclusions are reinforced from what emerges from the following Tables 12.6 and 12.7, where we replicated the overall estimation reported in the previous Tables 12.4 and 12.5, separately by manufacturing and service sectors (explained in Sect. 4.1.), and where we analyse more in depth the high-tech nature of the manufacturing sectors, differentiating between high-tech and non-high-tech manufacturing sectors (Sect. 4.2).

4.1 Manufacturing Versus Service Sectors

Tables 12.4 and 12.5 show the results for the analysis splitting the sample in manufacturing and service firms located in higher- and lower-order R&D regions, respectively. As can be seen – focusing on the more reliable FE- and RE-estimated coefficients – in both manufacturing and service sectors, the R&D-intensive regions are characterised by larger R&D coefficients in comparison with the other regions. This is a confirmation of the "increasing return" hypothesis. Furthermore, the higher R&D/productivity elasticities are displayed by the firms belonging to the service sectors and located in the high-order R&D regions (0.096 and 0.118).

Turning the attention to capital formation and embodied technological change, an unambiguous outcome clearly merges: In all the economic sectors, the weakly innovative European regions strongly rely on embodied technological change with a capital/productivity elasticity that is always larger than the one estimated within the firms located in the R&D-intensive regions.

4.2 High-Tech Versus Non-high-tech Manufacturing Sectors

In Tables 12.6 and 12.7, the focus is in the differences between high-tech manufacturing firms located in higher-order or lower-order regions and differences between non-high-tech manufacturing firms located in lower-order regions.

Table 12.6 results show what other previous evidence showed, the way R&D investments affect productivity in high-tech industries appears to be affected by the environment where the firm operates. Our results support the hypothesis that firms belonging to manufacturing sectors with higher requirements of investments (high-tech ones) would get more from their investments if they are located in a favourable environment for R&D and innovation. High-tech manufacturing firms, characterised by higher requirements of knowledge capital, get more from their investments in R&D

Table 12.3 Higher-order versus lower-order European NUTS (regional BERD/GDP>= 1.8% is the threshold)

	Whole sample			Higher-order R&D NUTS regions			Lower-order R&D NUTS regions		
	POLS	FE	RE	POLS	FE	RE	POLS	FE	RE
Log(R&D stock per employee)	0.144***	0.057***	0.073***	0.160***	0.072***	0.087***	0.119***	0.044***	0.057***
	(0.013)	(0.011)	(0.009)	(0.020)	(0.016)	(0.014)	(0.019)	(0.015)	(0.013)
Log(physical stock per employee)	0.122***	0.053***	0.079***	0.091***	–0.010	0.031***	0.145***	0.093***	0.111***
	(0.012)	(0.011)	(0.010)	(0.018)	(0.017)	(0.015)	(0.017)	(0.014)	(0.014)
Log(employees)	0.014**	–0.162***	–0.056***	0.037***	–0.174***	–0.054***	–0.002	–0.166***	–0.064***
	(0.007)	(0.017)	(0.011)	(0.011)	(0.024)	(0.017)	(0.010)	(0.023)	(0.016)
Constant	–1.642***	3.751***	–1.151	3.835***	3.637***	3.210***	–1.116***	3.739***	3.777***
	(0.165)	(0.079)	(1.016)	(0.134)	(0.202)	(0.487)	(0.187)	(0.169)	(0.752)
Wald time dummies	1.89**	2.35***	17.34	1.80**	3.04***	25.50*	1.08	0.58	9.37
(p-value)	(0.014)	(0.001)	(0.431)	(0.022)	(0.000)	(0.084)	(0.365)	(0.910)	(0.950)
Wald country dummies	17.38***	–	27.02*	6.52***	–	16.76**	15.36***	–	15.51
(p-value)	(0.000)		(0.057)	(0.000)		(0.019)	(0.000)		(0.415)
Wald sectoral dummies	100.42***	–	88.02***	38.35***	–	40.62	82.94***	–	87.00***
(p-value)	(0.000)		(0.000)	(0.000)		(0.274)	(0.000)		(0.000)
R^2 (overall)	0.28	0.01	0.18	0.26	0.01	0.15	0.38	0.01	0.30
No. of observations	3,431			1,827			1,604		
No. of firms	626			328			298		

Notes: (Robust in POLS) standard errors in parentheses; *significance at 10%, **5%, ***1%

– For time dummies, country dummies and sectoral dummies, Wald test of joint significance are reported

Table 12.4 Higher-order versus lower-order European NUTS: manufacturing sectors

	Whole sample			Higher-order R&D NUTS regions manufacturing sectors			Lower-order R&D NUTS regions manufacturing sectors		
	POLS	FE	RE	POLS	FE	RE	POLS	FE	RE
Log(R&D stock per employee)	0.144***	0.057***	0.073***	0.129***	0.068***	0.084***	0.128***	0.038**	0.053***
	(0.013)	(0.011)	(0.009)	(0.021)	(0.020)	(0.018)	(0.023)	(0.016)	(0.015)
Log(physical stock per employee)	0.122***	0.053***	0.079***	0.115***	0.002	0.044**	0.167***	0.098***	0.120***
	(0.012)	(0.011)	(0.010)	(0.022)	(0.021)	(0.020)	(0.020)	(0.017)	(0.016)
Log(employees)	0.014**	–0.162***	–0.056***	0.056***	–0.149***	–0.008	–0.004	–0.193***	–0.072***
	(0.007)	(0.017)	(0.011)	(0.012)	(0.033)	(0.021)	(0.011)	(0.027)	(0.018)
Constant	–1.642***	3.751***	–1.151	3.685***	3.744***	0.730	2.837***	3.740***	1.208
	(0.165)	(0.079)	(1.016)	(0.220)	(0.223)	(0.776)	(0.251)	(0.104)	(1.053)
Wald time dummies	1.89**	2.35***	17.34	1.37	2.15***	24.27	1.17	0.77	8.88
(p-value)	(0.014)	(0.001)	(0.431)	(0.143)	(0.000)	(0.146)	(0.284)	(0.735)	(0.944)
Wald country dummies	17.38***	–	27.02*	34.02***	–	7.69	21.80***	–	18.34
(p-value)	(0.000)		(0.057)	(0.000)		(0.361)	(0.000)		(0.245)
Wald sectoral dummies	100.42***	–	88.02***	8.21***	–	25.53	13.22***	–	36.43*
(p-value)	(0.000)		(0.000)	(0.000)		(0.489)	(0.000)		(0.065)
R^2 (overall)	0.28	0.01	0.18	0.27	0.01	0.17	0.39	0.02	0.29
No. of observations	3,431			1,358			1,278		
No. of firms	626			238			225		

Notes: (Robust in POLS) standard errors in parentheses; *significance at 10%, **5%, ***1%
– For time dummies, country dummies and sectoral dummies, Wald test of joint significance are reported

Table 12.5 Higher-order versus lower-order European NUTS: service sectors

	Whole sample			Higher-order R&D NUTS regions Service sectors			Lower-order R&D NUTS regions Service sectors		
	POLS	FE	RE	POLS	FE	RE	POLS	FE	RE
Log(R&D stock per employee)	0.144***	0.057***	0.073***	0.207***	0.096***	0.118***	0.059**	0.068	0.056*
	(0.013)	(0.011)	(0.009)	(0.032)	(0.029)	(0.024)	(0.027)	(0.043)	(0.029)
Log(physical stock per employee)	0.122***	0.053***	0.079***	0.056**	–0.007	0.008	0.088***	0.089**	0.098***
	(0.012)	(0.011)	(0.010)	(0.028)	(0.033)	(0.030)	(0.033)	(0.035)	(0.030)
Log(employees)	0.014**	–0.162***	–0.056***	–0.006***	–0.199***	–0.123***	–0.008	–0.081***	–0.024
	(0.007)	(0.017)	(0.011)	(0.023)	(0.040)	(0.029)	(0.022)	(0.051)	(0.031)
Constant	–1.642***	3.751***	–1.151	4.601***	3.706***	3.439***	–0.025	3.469***	2.987***
	(0.165)	(0.079)	(1.016)	(0.336)	(0.204)	(0.700)	(0.346)	(0.426)	(0.859)
Wald time dummies	1.89**	2.35***	17.34	1.40	1.20	17.76	1.94**	0.24	5.28
(p-value)	(0.014)	(0.001)	(0.431)	(0.132)	(0.258)	(0.404)	(0.016)	(0.991)	(0.980)
Wald country dummies	17.38***	–	27.02*	14.42***	–	14.02**	4.43***	–	61.55***
(p-value)	(0.000)		(0.057)	(0.000)		(0.029)	(0.000)		(0.000)
Wald sectoral dummies	100.42***	–	88.02***	10.81***	–	23.22***	67.34***	–	10.86
(p-value)	(0.000)		(0.000)	(0.000)		(0.002)	(0.000)		(0.285)
R^2 (overall)	0.28	0.01	0.18	0.36	0.05	0.26	0.44	0.03	0.41
No. of observations	3,431			469			326		
No. of firms	626			90			73		

Notes: (Robust in POLS) standard errors in parentheses; *significance at 10%, **5%, ***1%
– For time dummies, country dummies and sectoral dummies, Wald test of joint significance are reported

Table 12.6 Higher-order versus lower-order European NUTS: high-tech manufacturing sectors

	Whole sample			Higher-order R&D NUTS regions High-tech manufacturing sectors			Lower-order R&D NUTS regions High-tech manufacturing sectors		
	POLS	FE	RE	POLS	FE	RE	POLS	FE	RE
Log(R&D stock per employee)	0.144***	0.057***	0.073***	0.109***	0.097***	0.095***	0.188***	0.035	0.054***
	(0.013)	(0.011)	(0.009)	(0.034)	(0.033)	(0.030)	(0.051)	(0.023)	(0.022)
Log(physical stock per employee)	0.122***	0.053***	0.079***	0.143***	0.004	0.067**	0.135***	0.050**	0.072***
	(0.012)	(0.011)	(0.010)	(0.036)	(0.037)	(0.032)	(0.036)	(0.024)	(0.024)
Log(employees)	0.014**	–0.162***	–0.056***	0.085***	–0.131***	0.018	0.002	–0.190***	–0.065**
	(0.007)	(0.017)	(0.011)	(0.016)	(0.050)	(0.033)	(0.020)	(0.042)	(0.030)
Constant	–1.642***	3.751***	–1.151	1.802***	3.436***	2.633***	3.780***	3.530***	0.057
	(0.165)	(0.079)	(1.016)	(0.201)	(0.431)	(1.012)	(0.150)	(0.163)	(0.440)
Wald time dummies	1.89**	2.35***	17.34	6.05***	1.03	10.92	2.35***	2.38***	47.71***
(p-value)	(0.014)	(0.001)	(0.431)	(0.000)	(0.423)	(0.860)	(0.001)	(0.001)	(0.000)
Wald country dummies	17.38***	–	27.02*	9.01***	–	4.52	5.37***	–	11.48
(p-value)	(0.000)		(0.057)	(0.000)		(0.718)	(0.000)		(0.404)
Wald sectoral dummies	100.42***	–	88.02***	9.19***	–	9.19	10.17***	–	6.33
(p-value)	(0.000)		(0.000)	(0.000)		(0.163)	(0.000)		(0.275)
R^2 (overall)	0.28	0.01	0.18	0.25	0.01	0.16	0.40	0.01	0.24
No. of observations	3,431			688			529		
No. of firms	626			114			96		

Notes: (Robust in POLS) standard errors in parentheses; *significance at 10%, **5%, ***1%
– For time dummies, country dummies and sectoral dummies, Wald test of joint significance are reported

Table 12.7 Higher-order versus lower-order European NUTS: other manufacturing sectors

	Whole sample			Higher-order R&D NUTS regions Other manufacturing sectors			Lower-order R&D NUTS regions Other manufacturing sectors		
	POLS	FE	RE	POLS	FE	RE	POLS	FE	RE
Log(R&D stock per employee)	0.144***	0.057***	0.073***	0.141***	0.024	0.059***	0.065***	0.040*	0.047**
	(0.013)	(0.011)	(0.009)	(0.019)	(0.021)	(0.019)	(0.020)	(0.022)	(0.020)
Log(physical stock per employee)	0.122***	0.053***	0.079***	0.085***	0.006	0.027	0.203***	0.140***	0.176***
	(0.012)	(0.011)	(0.010)	(0.020)	(0.021)	(0.020)	(0.025)	(0.025)	(0.022)
Log(employees)	0.014**	−0.162***	−0.056***	0.001	−0.166***	−0.043	−0.023	−0.262***	−0.094***
	(0.007)	(0.017)	(0.011)	(0.013)	(0.042)	(0.027)	(0.015)	(0.039)	(0.024)
Constant	−1.642***	3.751***	−1.151	4.311***	3.789***	3.919***	2.784***	3.906***	1.976
	(0.165)	(0.079)	(1.016)	(0.221)	(0.283)	(0.737)	(0.246)	(0.150)	(0.746)
Wald time dummies	1.89**	2.35***	17.34	1.76**	2.60***	28.31**	0.92	0.66	19.08
(p-value)	(0.014)	(0.001)	(0.431)	(0.029)	(0.000)	(0.041)	(0.552)	(0.844)	(0.387)
Wald country dummies	17.38***		27.02*	4.78***		6.38	27.22***		16.67
(p-value)	(0.000)	–	(0.057)	(0.000)	–	(0.496)	(0.000)	–	(0.214)
Wald sectoral dummies	100.42***	–	88.02***	49.73***	–	32.26**	12.85***	–	37.98***
(p-value)	(0.000)		(0.000)	(0.000)		(0.040)	(0.000)		(0.006)
R^2 (overall)	0.28	0.01	0.18	0.39	0.01	0.17	0.45	0.01	0.38
No. of observations	3,431			670			749		
No. of firms	626			124			129		

Notes: (Robust in POLS) standard errors in parentheses; *significance at 10%, **5%, ***1%
– For time dummies, country dummies and sectoral dummies, Wald test of joint significance are reported

if they are located in higher-order regions. Regarding the physical capital returns on firm productivity, they are also positive and significant, showing their importance in high-tech manufacturing firms' productivity. We can conclude that this particular set of firms show, no matter the type of investment, gains on labour productivity.

The results address additional conclusions; high-tech manufacturing sectors operating in lower-order regions obtain higher gains for the physical capital than high-tech manufacturing firms located in higher-order regions.

It is worth noticing that time does not affect the productivity for the high-tech manufacturing firms located in higher-order regions, while for firms that are located in lower-order regions, the macroeconomic conditions of the cycle affect the labour productivity of these particular samples.

Table 12.7 contains the results of the samples of firms belonging to non-high-tech manufacturing sectors and located in higher-order and lower-order R&D regions, respectively. As we can see, non-high-tech firms appear to gain more for their physical capital investments when they are located in a less favourable R&D environment. When firms belonging to a non-high-tech manufacturing sector locate themselves in a more dynamic and innovative environment, the only investment that appears to be determinant is the knowledge capital. Firms that operate in a more competitive environment are forced to maintain higher levels of knowledge investments and higher production of innovation in order to maintain their levels of competitiveness (and survive and grow). In any case, their investments show higher returns in comparison with firms operating in a more hostile environment.

The non-high-tech manufacturing firms show the highest returns from their investments in physical capital when they are operating in non-R&D-intensive regions; embodied technical change is still playing an important role in this set of firms.

For the non-high-tech firms, the sectoral composition of the environment appears to be determinant in explaining the labour productivity differences when they operate in lower-order regions. In general, industrial structure characterising each region might affect the R&D productivity relationship. This issue has not been yet largely analysed in the literature. In the case of non-high-tech manufacturing firms operating in higher-order regions, macroeconomic conditions appear to be more significant in explaining productivity gains.

On the whole, in Europe, productivity growth in medium- and low-tech sectors and in the less innovative regions is still heavily dependent on investment in physical capital (embodied technological change), while knowledge capital or intangibles seem to play a secondary role.

Hence, we can further confirm and specify what has been already discussed commenting on the sectoral results reported in the Tables 12.4 and 12.5. In the EU, the investment in physical capital is significantly linked to productivity gains, confirming the hypothesis advanced in this study that "embodied technological change" is a crucial driver of productivity evolution. While this contribution is similar to the one offered by the R&D expenditures in aggregate, when we only consider either the manufacturing non-high-tech sectors (Table 12.7) or the non-R&D-intensive European regions (Tables 12.3, 12.4, 12.5, 12.6 and 12.7; panel 3, columns 2 and 3), the capital coefficient systematically exceeds the correspondent R&D coefficient.

5 Conclusions and Policy Implications

The results of this study show that the returns of the R&D investments on firm performance are higher for firms located in the European regions with a more favourable innovative environment and, among them, for firms belonging to high-tech sectors.

Our results also emphasise the relevant role in firm productivity of physical capital investments in certain firms. In particular, physical capital is still playing an important role in explaining the productivity gains of manufacturing firms located in lower-order regions or belonging to non-high-tech sectors.

The particular nature of the relationship between R&D and capital formation on the one hand and productivity evolution on the other hand might heavily be affected by the industrial structure which characterises a single region. Thus – according to what discussed above – a region characterised by a large presence of high-tech sectors would probably turn out to be very sensitive to R&D activities in getting productivity gains, while a region characterised by a disproportionate presence of traditional sectors, mainly composed by SMEs, would come out to be particularly responsive to firm capital formation.

In terms of policy implications, a European regional policy targeted to increase the competitiveness and productivity of European countries by means of increasing the R&D investment (with strategies like the Lisbon Agenda or the Innovation Union) should not leave aside the strong heterogeneity across European regions. Therefore, there is no single formula to promote efficient innovation in all regions, but more systematic policy analysis would help policymakers to understand which region-level instruments help firms to generate innovation in increasing their regional competitiveness and growth.

Regional policy of innovation should, in general, focus on emphasising absorption capacity and innovation by adoption. By encouraging and incentivising labour mobility, attracting private capital, improving the accessibility and connectivity and promoting endogenous growth by identifying potential sources of growth, the possibilities of the regions to attract high-tech firms will increase.

Acknowledgement Financial and data support from the “Corporate R&D and Productivity: Econometric Tests Based on Microdata” JRC-IPTS project is gratefully acknowledged. Part of the work done in this chapter was carried out, while some authors were staff at the European Commission, Joint Research Centre (JRC), Institute for Prospective Technological Studies (IPTS), Seville, Spain.

Appendix

Table 12.8 Distribution of firms and observations across countries

Country	Firms	Observations
Austria	16	51
Belgium	20	82
Czech Republic	1	4
Denmark	21	152
Estonia	1	3
Finland	41	157
France	54	279
Germany	141	749
Greece	11	41
Hungary	3	12
Ireland	8	55
Italy	5	19
Luxembourg	3	9
Netherlands	25	165
Slovenia	1	4
Spain	3	7
Sweden	62	386
United Kingdom	223	1,299

References

Aghion P, Howitt P (1992) A model of growth through creative destruction. Econometrica 60(2):232–251

Antonelli C (2010) Pecuniary externalities and the localized generation of technological knowledge. In: Boschma R, Martin R (eds) The handbook of evolutionary economic geography. Edward Elgar, Cheltenham/Northampton

Audia PG, Freeman JH, Reynolds P (2006) Organizational foundings in community context: instruments manufacturers and their interrelationship with other organizations. Admin Sci Quart 51:381–419

Baldwin R, Forslid R (2000) The core-periphery model and endogenous growth: stabilizing and destabilizing integration. Economica 67:307–324

Boshma R, Frenken K (2009) Technological relatedness and regional branching. In: Bathelt H, Feldman M, Kloger D (eds) Dynamic geographies of knowledge creation and innovation. Routledge/Taylor and Francis, London

Bronzini R, Piselli R (2009) Determinants of long-run regional productivity with geographical spillovers: the role of R&D, human capital and public infrastructure. Reg Sci Urban Econ 39:187–199

Cantwell J, Iammarino S (1998) MNCs, technological innovation and regional systems in the EU: some evidence in the Italian case. Int J Econ Bus 5:383–408

Cantwell J, Iammarino S (2000) Multinational corporations and the location of technological innovation in the UK regions. Reg Stud 34:317–322

Cantwell J, Iammarino S (2001) EU regions and multinational corporations: change, stability and strengthening of technological comparative advantages. Ind Corp Change 10:1007–1039

Carroll GR, Hannan MT (2000) The demography of corporations and industries. Princeton University Press, Princeton

Cohen CW, Levinthal DA (1990) Absorptive capacity: a new perspective on learning and innovation. Admin Sci Quart 35:128–152

Cooke P, Gómez Uranga M, Etxebarria G (1997) Regional innovation systems: institutional and organisational dimensions. Res Policy 26:475–491

Crépon B, Duguet E, Mairesse J (1998) Research, innovation, and productivity: an econometric analysis at firm level. Econ Innov New Tech 7:115–158

Cuneo P, Mairesse J (1983) Productivity and R&D at the firm level in French manufacturing. NBER working paper no. 1068

Dettori B, Marrocu E, Paci R (2008) Total factor productivity, intangible assets and spatial dependence in the European regions. CRENOS working paper, 2008/23

Feldman MP (1994) The geography of innovation. Economics of science, technology and innovation. Kluwer, Amsterdam

Fischer M, Scherngell T, Reismann M (2008) Knowledge spillovers and total factor productivity. Mimeo, paper presented at the ERSA conference, Liverpool

Forslid R, Wooton I (2003) Comparative advantage and the location of production. Rev Int Econ 11:588–603

Frenken K, van Oort F, Verburg T (2007) Related variety, unrelated variety and regional economic growth. Reg Stud 41:685–697

Griliches Z (1979) Issues in assessing the contribution of research and development to productivity growth. Bell J Econ 10:92–116

Griliches Z, Mairesse J (1982) Comparing productivity growth: an exploration of French and US industrial and firm data. NBER working paper no. 961

Grubbs F (1969) Procedures for detecting outlying observations in samples. Technometrics 11:1–21

Gumbau-Albert M, Maudos J (2006) Technological activity and productivity in the Spanish regions. Ann Regional Sci 40:55–80

Hall BH (2007) Measuring the returns to R&D: the depreciation problem. NBER working paper no. 13473

Hall BH, Mairesse J (1995) Exploring the relationship between R&D and productivity in French manufacturing firms. J Econometrics 65:263–293

Hannan MT, Carroll GR, Dutton EA, Torres JC (1995) Organizational evolution in a multinational context: entries of automobiles manufacturers in Belgium, Britain, France, Germany and Italy. Am Sociol Rev 60:509–528

Harhoff D (1998) R&D and productivity in German manufacturing firms. Econ Innov New Tech 6:29–49

Hatzichronoglou T (1997) Revision of the high-technology sector and product classification. OECD, Paris

Hulten CR (1990) The measurement of capital. In: Berndt E, Triplett J (eds) Fifty years of economic management. University of Chicago Press, Chicago

Iammarino S, McCann P (2010) The relationship between multinational firms and innovative clusters. In: Boschma B, Martin R (eds) The handbook of evolutionary economic geography. Edward Elgar, Cheltenham

Jorgenson DW (1990) Productivity and economic growth. In: Berndt E, Triplett J (eds) Fifty years of economic management. University of Chicago Press, Chicago

Klepper S (2007) Disagreements, spinoffs, and the evolution of Detroit as the capital of the U.S. automobile industry. Manage Sci 53:616–631

Kline SJ, Rosenberg N (1986) An overview of innovation. In: Landau R, Rosenberg N (eds) The positive sum strategy: harnessing technology for economic growth. National Academy Press, Washington, DC

Krugman P (1991) Increasing returns and economic geography. J Polit Econ 99:483–499

Krugman P, Venables AJ (1996) Integration, specialization, and adjustment. Eur Econ Rev 40:959–967

Kwon HU, Inui T (2003) R&D and productivity growth in Japanese manufacturing firms. ESRI Discussion Paper Series No. 44, Tokyo
Le Bas C, Sierra C (2002) Location versus home country advantages in R&D activities: some further results on multinationals' location strategies. Res Policy 31:589–609
Lucas R (1988) On the mechanics of economic development. J Monetary Econ 22:3–42
Lundvall BA (1988) Innovation as an interactive process: from user-producer interaction to the national system of innovation. In: Dosi G, Freeman C, Nelson R, Silverberg G, Soete L (eds) Technical change and economic theory. Pinter, New York
Malmberg A, Maskell P (1997) Towards an explanation of industry agglomeration and regional specialization. Eur Plann Stud 5:25–41
Malmberg A, Maskell P (2002) The elusive concept of localization economies - towards a knowledge-based theory of spatial clustering. Environ Plann A 34:429–449
Marshall A (1890) Principles of economics. Macmillian, London
Martin P, Ottaviano G (2001) Growth and agglomeration. Int Econ Rev 42:947–968
Maskell P (2001) The firm in economic geography. Econ Geogr 77(4):329–344
Nadiri M, Prucha I (1996) Estimation of the depreciation rate of physical and R&D capital in the US total manufacturing sector. Econ Inq 34:43–56
OECD (2002) Frascati manual - proposed standard practice for surveys on research and experimental development. OECD, Paris
OECD (2009a) Regions matter. Economic recovery, innovation and sustainable growth. OECD, Paris
OECD (2009b) How regions grow. Trends and analysis. OECD, Paris
Ortega-Argilés R, Piva M, Potters L, Vivarelli M (2010) Is corporate R&D investment in high-tech sectors more effective? Contemp Econ Pol 28:353–365
Ortega-Argilés R, Potters L, and M. Vivarelli (2011) R&D and Productivity: Testing Sectoral Peculiarities Using Micro Data. Empirical Economics 41(3):817–839
Parisi M, Schiantarelli F, Sembenelli A (2006) Productivity, innovation creation and absorption, and R&D. Microevidence for Italy. Eur Econ Rev 50:2037–2061
Patel P, Vega M (1999) Patterns of internationalization of corporate technology: location versus home country advantages. Res Policy 28:145–155
Porter M (1990) The competitive advantage of nations. Free Press, New York
Porter M (1998) Clusters and the new economics of competition. Harv Bus Rev 76:77–90
Porter M (2000) Location, competition, and economic development: local clusters in a global economy. Econ Dev Q 14:15–34
Rincon A, Vecchi M (2003) Productivity performance at the company level. In: O'Mahony M, Van Ark B (eds) EU productivity and competitiveness: an industry perspective. Can Europe Resume the Catching-up Process? European Commission, Luxembourg
Romer P (1986) Increasing returns and long-run growth. J Polit Econ 94:1002–1037
Romer P (1987) Growth based on increasing returns due to specialization. Am Econ Rev 77:56–62
Romer P (1990) Endogenous technical change. J Polit Econ 99:72–102
Segarra A (2010) Innovation and productivity in manufacturing and service firms in Catalonia: a regional approach. Econ Innov New Tech 19:233–258
Stefansky W (1972) Rejecting outliers in factorial designs. Technometrics 14:469–479
Verspagen B (1995) R&D and productivity: a broad cross-section cross-country look. J Prod Anal 6:117–135
von Hippe E (1988) The sources of innovation. Oxford University Press, New York
Wakelin K (2001) Productivity growth and R&D expenditure in UK manufacturing firms. Res Policy 30:1079–1090