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Abstract

In this paper we quantitatively review the empirical literature on spatial knowledge spillovers in Europe by means of meta-analysis to determine the extent to which such spillovers have been empirically documented as well as the spatial reach of these spillovers. In addition, we will apply meta-regression analysis to analyze the determinants of observed heterogeneity across and between publications. To our knowledge this is the first study of its kind. Our results show that if total local R&D expenditure in a European region increases by 1%, then the number of patents in that region, on average, increases by about 0.5%. Spatial knowledge spillovers induce a positive effect on local knowledge production, however, this effect proves to be small around 0.07%. Spatial weighting regime seems to matter. If R&D expenditures in other regions are weighted by distance in kilometers or minutes (instead of a binary contiguity matrix) then the spillover effect on average will be larger. Also, public R&D expenditure is found to have a lower impact on local patent production compared to the private R&D expenditure.

Keywords: knowledge spillovers, knowledge externalities, meta-analysis, Europe

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1 Introduction

During the last decade, we have been able to observe a veritable explosion in the interest in the topic 'knowledge spillovers'. A search with Google Scholar on the 7th of April 2011 limited to "Business, Administration, Finance and Economics" gave 18,000 hits of which more than 70 per cent was from the period 2002-2011. This explosive increase in interest in the concept among researchers mirrors both an increased scientific interest and an increased interest among policy makers in the topic. The increased interest among researchers is undoubtedly stimulated by the developments in endogenous growth theory during the two last decades. Among policy makers, we can trace a substantially increased interest in the topic 'knowledge spillovers' not least among policy makers within Europe. Actually, 75 per cent of the 18,000 hits contain the word Europe. In Europe, it is in particular within the European Union (EU) that 'knowledge spillovers' have come into focus. The Lisbon agenda confirmed by EU leaders in March 2000, which aims to create a climate in Europe that stimulates innovation, competitiveness and economic growth, has put up 'knowledge spillovers' on the European policy agenda.

The earliest reference to 'knowledge spillovers' that we have been able to find is Griliches and Lichtenberg (1984, p.466), who defines 'pure knowledge spillovers' as "the cross-fertilization of one industry's research program by developments occurring in other industries", i.e. as inter-industry spillovers. However, it should be observed that research and development 'spillovers' was discussed already in, for example, Griliches (1979). These early contributions to the study of knowledge spillovers were all disregarding the effect of 'the tyranny of distance' on knowledge spillovers, i.e. they were non-spatial. It was not until the 1990s that researchers started to study the geographical extent of knowledge spillovers (Jaffe et al 1993; Audretsch and Feldman 1996). We have found the first use of the term 'inter-regional knowledge spillovers' in Premer and Walz (1994), the first use 'regional knowledge spillovers' in Englmann and Walz (1995), the first use of 'local knowledge spillovers' in Head et al (1995) and Englmann and Walz (1995). The first use of 'geographic knowledge spillovers' we found in Anselin et al (1997), the first use of 'spatial knowledge spillovers' in Keilbach (1998), the first use of 'intra-regional knowledge spillovers' in Dohse (2000) and the first use of 'geographical knowledge spillovers' in Wallsten (2001). In Table 1.1, we illustrate the total number of hits for all these terms according to Google Scholar the 10th of April 2011. We can observe that an overwhelming majority of the publications dealing with spatial aspects of knowledge spillovers also contains some kind of reference to Europe. The interest in spatial knowledge spillovers has its background in that the existence of localized knowledge spillovers is one possible explanation to the industrial clustering that we can observe (Krugman 1991 and 1998) – a clustering that is greater than would be expected if the geographic distribution of firms and jobs were random (Ellison and Glaeser 1997). Evidences of knowledge spillovers that are geographically bounded have been found in many studies (see e.g. Jaffe 1989 and Jaffe et al 1993). However, many existing studies have explored these issues only within large geographic units, such as nations, states or very large regions such as the NUTS 2 regions within EU, which has made it impossible more in detail to determine the spatial reach of knowledge spillovers (Wallsten 2001). Since firms in an industry normally cluster at a finer spatial scale even within cities and since the hypothesis is that firms located in proximity to each other benefit from knowledge spillovers, most studies give too little specific information about how distance as well as the local firm density matter for knowledge spillovers.

Table 1.1 Number of hits using Google Scholar April 10th 2011

Search term	Number of hits	Number of hits when Europe is added
Interregional knowledge spillovers	89	84
Inter-regional knowledge spillovers	47	44
Regional knowledge spillovers	345	289
Local knowledge spillovers	487	399
Geographic knowledge spillovers	122	93
Geographical knowledge spillovers	123	111
Spatial knowledge spillovers	293	193
Intraregional knowledge spillovers	8	8
Intra-regional knowledge spillovers	20	18

How can we then understand this big interest in spatial aspects of knowledge spillovers in general and in Europe, in particular? One obvious reason is the long-standing observation that regions also within integrated economic areas, such as the European Union tend to diverge rather than converge with regard to per capita incomes and labour productivity. This is of course puzzling not least for many economists. The observed patterns of divergence is not in line with the predictions of the spatial version of the neo-classical growth model, where mobility of capital and labour over the long run would even out differences between regions (Borts and Stein 1964). Neither are they in line with the more recent endogenous growth theory a la Romer (1986 and 1990) and Lucas (1993), which builds upon the presumption that new knowledge is instantaneously and freely available to all economic agents because knowledge is assumed automatically and instantaneously to spill over from the economic agent generating the knowledge to all other economic agents.

In a similar manner, Griliches (1992) perceived that knowledge would spill over from the economic agent investing in new knowledge to be used by other economic agents at low or no cost. Knowledge can spill over and thus generate externalities since it, being an intellectual asset, differs from other factors of production by being non-exclusive and non-rivalrous (Arrow 1962) and thus generating appropriability problems for those economic agents generating new knowledge. Even if knowledge can spill over, it does not imply that spillovers are automatic and instantaneous. New knowledge is highly uncertain and context specific and is primarily diffused by means of face-to-face interaction, which implies that the diffusion of new knowledge is associated with high transaction costs. Hence, early diffusion of new knowledge tends to be geographically limited to a spatial scale that allows frequent face-to-face interaction, which normally is equal to the daily interaction space of people. The spatial diffusion of knowledge is associated with frictions, which increase with distance, which gives a clear advantage to locations where knowledge generating activities for one reason or another started to cluster. However, economists have in the post-war period developed various explanations for divergent economic development in different regions, such as the theory of development poles (Perroux 1955), theories of cumulative causation in economic growth (Myrdal 1957; Dixon and Thirlwall 1975) and theories of economic agglomeration, such as the 'New Economic Geography' (Krugman 1991), which highlights the links between economic integration and agglomeration.

To understand the diverging development within the European Union and within its member states we need a theoretical framework that is able to explain the interaction between economic integration, the location of peoples and economic activities, and long-run growth in a system of regions. That growth affects location and location affects growth has strong theoretical foundations. In principle, it is a basic characteristic of all endogenous growth models that they depend upon technical externalities in the form of knowledge spillovers or production externalities. That such externalities are connected with the spatial distribution of R&D activities and/or production has been documented empirically (see Eaton and Kortum (1996)). It is against this background natural to assume that agglomeration of production and/or R&D activities will stimulate growth as well as that growth will stimulate agglomeration of production and/or R&D due to the existence of the actual externalities.

Thus, there exists a theoretical framework capable at explaining the dynamic interaction between location and growth in a system of regions, when externalities are present. However, to understand the importance of the actual externalities and spatial scale at which they operate, we need detailed empirical studies. Thus, there is a need to establish the pervasiveness of externalities based upon geographical proximity as well as the distances over which they operate (cf. Head et al (1995)). In the sequel, we will focus on one type of such externalities, namely knowledge spillovers. The empirical studies of the effects of knowledge spillovers in Europe have normally focused on the localized effects on either total factor productivity or knowledge production measured in terms of patent output.

The purpose of this paper is to review quantitatively the empirical literature on spatial knowledge spillovers in Europe by means of meta-analysis to determine the extent to which such spillovers have been empirically documented as well as the spatial reach of these spillovers. In addition, we will apply meta-regression analysis to analyze the determinants of observed heterogeneity across and between studies. Thoroughly assessed empirical information on these issues is particularly important for the design of policies at the EU, the national and the regional level aimed at increasing knowledge production and economic growth.

Meta-analysis can be described as a set of statistical and econometric methods that can be used to summarize, analyze and evaluate the empirical results from a set of primary studies focusing on a specific research question (Stanley and Jarrell 1989; Stanley 2001). It offers a more systematic and objective way to evaluate the results from a number of empirical studies compared to conventional literature reviews, which have difficulties in comparing different empirical studies due to differences in theoretical frameworks, empirical models, econometric methods and data definitions. Meta-analysis makes it possible to analyze statistically the variation over studies by means of basic economic variables and variations in research design. By applying meta-analysis on empirical studies of knowledge spillovers in Europe, we will be able to estimate the effect of knowledge spillovers on total factor productivity and knowledge production in Europe as well as the spatial reach of these effects, which is of great interest to policy makers in Europe interested in promoting economic growth in Europe.

The outline of this paper is as follows: Section 2 discusses spatial knowledge spillovers by definition and methodological approaches. Section 3 presents the meta-analysis, some stylized facts of the meta-sample and the results from gathering the data for the meta-regression analysis. In addition, it gives an overview of the meta-sample and descriptive statistics from the publications that have been analyzed in order to obtain a sample. Section 4 comprises of the meta-regression analysis, where our methodology, empirical model and analysis are presented. Two models are estimated, one for local knowledge effects and the other for interregional knowledge spillover effects. The final section concludes this paper.

2 Spatial Knowledge Spillovers

2.1 Definitions

Griliches (1979, p. 104) describes 'knowledge spillovers' as "working on similar things and hence benefiting much from each other's research". However, there is of course no guarantee that both parties gain or even gain equally, when knowledge diffuse between economic agents. The principal idea behind the use of the concept 'knowledge spillovers' is that they are associated with externalities, i.e. that knowledge generated by one economic agent can be used by other economic agents without any compensation paid to the generating economic agent who has carried the costs for the knowledge generation. However, it is important that knowledge may flow because of knowledge-transactions or as a by-product of other transactions and that 'pure knowledge spillovers' only make up a part or possibly a minor part of all knowledge flows. The implication is that not all knowledge flows are associated with externalities (Breschi and Lissoni 2009).

Karlsson and Johansson (2006) argue that from the perspective of a firm one can make a separation of three groups of knowledge flows, which may generate knowledge spillovers: (i) transaction-based knowledge flows, (ii) transaction-related knowledge flows, and (iii) pure knowledge spillovers.[1] The three categories are presented in Table 2.1 together with nine types of knowledge flows.

[1] Griliches (1979) makes a distinction between pure knowledge spillovers and rent spillovers, where the latter arise because new goods and services are purchased at less than their fully quality adjusted prices. Transaction-related knowledge flows here represent rent spillovers.

Table 2.1 Classification of knowledge flows to a firm

Knowledge flow category	Knowledge flow type
Transaction-based flows:	Flows from knowledge providers that sell knowledge that is used as an input to a firm's R&D activities Flows in the form of inventions (innovations) that are sold to a firm (e.g., by licensing a patent) Knowledge flows between firms that cooperate in an R&D project, where costs and benefits are regulated by an explicit or an implicit contract, which may or may not be associated with unintentional knowledge spillovers A firm obtains access to knowledge via a merger or an acquisition
Transaction-related flows:	A flow of knowledge that is embodied in the delivery of inputs from an input supplier to a firm In the course of supplying inputs to a firm, knowledge from the input supplier spills over unintentionally to the input-buying firm In the course of supplying inputs to a firm, knowledge from the input-buying firm spills over unintentionally to the input-selling firm
Pure spillover flows:	Unintentionally, knowledge spills over from one firm to a competing firm in the same industry Unintentionally, knowledge spills over between firms belonging to different industries

Source: Karlsson and Johansson (2006)

From a firm's point of view, one can make a distinction between upstream, downstream and horizontal knowledge and technology flows. Upstream knowledge flows are helpful in generating access to suppliers' knowledge and technology often embedded in inputs bought by a firm. Downstream knowledge flows include the sale of knowledge and technology to customers either as licenses or as embedded in products. Horizontal knowledge and technology flows include intended and unintended knowledge and technology flows between firms in the same industry. Upstream and downstream knowledge and technology flows are inter-sectoral, while horizontal knowledge and technology flows are intra-sectoral.

From Table 2.1 it is obvious that the extent to which knowledge flows are associated with 'externalities' obviously varies a lot between the different types of knowledge flows. It is also clear from the table that 'knowledge spillovers' and thus 'externalities' may exist also in cases where market mechanisms are operating. To the extent that knowledge flows are connected with externalities, we may make a distinction between three types of externalities, which also are the three main agglomeration forces according to the "new economic geography" approach:

- Pecuniary externalities, i.e. externalities due to market interactions
- Technological externalities, i.e. externalities due to non-market interactions
- Human capital externalities, e.g. externalities due to the mobility between firms of employees with embodied knowledge

Breschi and Lissoni (2001) argue that it is important to improve the understanding of the transmission mechanisms of knowledge in addition to measure knowledge spillovers by a rather limited set of indicators. There exist several mechanisms, which support and facilitate the transfer and diffusion of tacit as well as codified knowledge (cf. Arrow 1994) and technology:

- education,
- communication channels that are interactive and have a high bandwidth,
- deliberate policy (e.g., organizations setting up scouting and knowledge intelligence units),
- R&D collaboration,
- special activities of people in order to obtain and disseminate knowledge (e.g. gatekeepers, see Allen 1977),
- mobility of people with the relevant knowledge and skills,
- trade in goods and services,
- trade in knowledge and technologies,
- direct investments,
- intra-firm knowledge management, and
- imitation and reverse engineering (cf. Verspagen 1994).

It is important to observe that even if each of these channels or mechanisms can be seen as partly independent, they are often linked to each other in different ways. It is in this connection important to observe that also international collaborations are a significant and increasingly important channel for transfer of knowledge and technology in both the private and the public sector (Archibugi and Coco 2004). An increasing number of partnerships among firms, universities and public research centers as well as between individual researchers and inventors is a clear indication of the growing importance of collaboration (NSF 2002). Collaboration permits the partners to share and acquire the expertise of each other, thus enriching the overall know-how. It can function as a positive sum game, where the advantages outweigh the disadvantages even if the advantages are not always equally shared among partners (Archibugi and Lundvall

2001, Eds.). The total number and type of collaborations can be taken as a measure on the one hand of the vitality of the regional, national and international knowledge systems and on the other hand as an indicator of the extent and types of knowledge and technology transfers. The attractiveness of the knowledge base of economic agents will determine the extent to which they are invited to participate in collaborative ventures.

However, due to spatial frictions, we can expect that different mechanisms for the transfer of knowledge and technology differ in their effectiveness in transferring knowledge and technology at different distances. As much knowledge and technology tend to have a degree of tacitness, to be highly complex and/or contextual, it is often assumed that knowledge spillovers are bounded in geographical space. This implies that it is important to understand why location matters for knowledge flows of different kinds (Autant-Bernard et al 2007). We need not only to understand the spatial reach of knowledge flows but also their time profile. There is also a need to understand the mechanisms by which different types of knowledge and technologies are transferred, why transfer is unequal over space and the implications in terms of innovative performance in different locations. To achieve a better understanding of knowledge flows and the mechanisms that stimulate innovation performance, there is a need to evaluate by means of meta-analyses the results of the numerous empirical studies of knowledge spillovers performed in recent years. Certainly, such a meta-analysis is not enough to understand why and how location matters. There is also a need for complementary analyses of phenomena such as mobility of researchers, foreign direct investments, R&D collaborations, imports of knowledge-intensive products and entrepreneurial activities using micro-data (Audretsch and Feldman 2004). Furthermore, to evaluate fully the impact of the spatial dimension it is important also to consider the influence of other proximities than the geographical, such as technological, institutional, organizational and social proximity. However, at least the three last of these proximities are a function of among other things the geographical proximity.

2.2 Methodologies Employed in the Literature

2.2.1 Different Methodological Approaches

Studies of spatial knowledge spillovers fall within the study field 'geography of innovation' (Karlsson and Manduchi 2001; Audretsch and Feldman 2004). One common approach here has been to estimate how the knowledge output of firms in different locations is influenced by the research and innovation activities of other firms in the same as well as other locations to determine the influence of proximity on knowledge output. The extent of knowledge flows and knowledge spillovers is generally measured by the patterns of patent and publication citations, technology licensing or the degree of co-patenting and co-publication activities of researchers at universities and research institutes and in industry (Jaffe et al 1993; Audretsch and Feldman 1996; Crespi et al 2006; Ponds et al 2007).[2]

Many researchers argue that patent citations can be used as a measure of technological impact and knowledge spillovers, in the sense that one specific technological innovation explicitly detects several others as being the technological state-of-the art on which it is based. Patent citations have been used to analyze questions concerning spatial knowledge spillovers (see e.g. Jaffe et al 1993) and spillovers from public research (Jaffe and Trajtenberg 1996; Jaffe and Lerner 1999). However, patent citations are by no means a perfect measure of knowledge spillovers or flows since citations to patents not known to the inventor(s) may be added in the patenting process. Thus, patent citations are a noisy measure but they have substantial information content (Jaffe et al 2000).

Many studies have focused on only disentangling the effects of 'pure' non-market 'knowledge spillovers', i.e. technological spillovers, but attempts have also been made to estimate the effects of market-based knowledge flows (Autant-Bernard and Massard 2007; Miguélez and Moreno 2010).

2.2.2 The Knowledge Production Function Approach

According to Feldman (1999), it is possible to categorize studies of knowledge effects in regions into four tracks: (i) geographic knowledge production functions, (ii) paper trails left in patent citations, (iii) ideas in people or (iv) ideas in goods. Studying the literature reveals a clear dominance for the use of geographic knowledge production functions and this approach is the focus of our meta-analysis. The framework for analyzing the importance of knowledge and knowledge spillovers on innovative activity is usually based on the knowledge production function (KPF) of Griliches (1979). Jaffe (1989) later developed the framework with a geographical dimension.

Spatial spillovers and spatial dependence can be accounted for in various ways. Following Anselin (2003), the spatial effects can be either (i) un-modeled, (ii) modeled or (iii) both un-modeled and modeled. If the spatial spillovers are global, i.e. every location is correlated with every other location, but the correlations decrease with distance, the inclusion of a spatial multiplier effect of the form $(I-\lambda W)^{-1}$ models the spatial effects. Equations (2.1) to (2.3) show the three structural forms.

[2] It is interesting to note that research on other types of linkages between universities and industry other than those related to patents and publications are rare, despite that other channels for knowledge flows and knowledge spillovers, such as consulting, contract research and training programs probably are more frequently used in practice (D'Este and Patel 2007; Link et al 2007).

Un-modeled effects: $y = x\beta + (I - \lambda W)^{-1}u,$ (2.1)

modeled effects: $y = (I - \lambda W)^{-1}x\beta + u,$ (2.2)

both effects: $y = (I - \lambda W)^{-1}x\beta + (I - \lambda W)^{-1}u,$ (2.3)

with $(I - \lambda W)^{-1} = I + \lambda W + \lambda^2 W^2 + \cdots$ and $|\lambda| < 1$.

y is the dependent variable, W is a spatial weight matrix, λ is a spatial autoregressive parameter, x is a matrix of independent variables, β is a vector of regression parameters and u is a vector of independent disturbance terms, $u \sim N(0, \sigma^2)$.[3]

The question is then which model to choose. The answer depends very much on the case under study. Let us assume that the objective is to find to what extent R&D can account for the variations in regions' patent production.

- If the interest is limited to the local effects of R&D, i.e. how R&D conducted in region *i* affects patent production in region *i*, then the answer is un-modeled effects.
- If the interest is to find both the local effects and the spatial spillovers of R&D, i.e. how patent production in region *i* is affected by R&D efforts in municipality *i*, *j*, *k*, …, then the answer is modeled effects.
- If the interest is to estimate local effects of R&D and spatial dependencies of patent production, i.e. how patent production in region *i* is affected by patent production in region *j*, *k*, … , then the answer is both effects.

Our focus is to find and investigate studies that estimate the importance of spatial spillovers of explanatory variables (i.e. studies with 'modeled effects').

[3] The model with the un-modeled effects is usually called the spatial error model. The model with both un-modeled and modeled effects is the so called spatial lag model.

3 A Simple Meta-Analysis

3.1 The Meta-Sample

The data for the meta-analysis on knowledge spillovers in Europe has been collected via an extensive search for publications that correspond to a set of lowest common denominators. The period analyzed ranges from 2000 to 2010. Keywords that have been used to find publications of interest comprise of: "*knowledge production function and Europe*" and/or "*knowledge spillovers and Europe*". Additional requirements made for a specific publication to be included in the analysis are: (i) Europe must be the focus area, (ii) it applies quantitative methods, (iii) it includes a minimum of five European countries (within and between) and (iv) that the publication must contain a specific knowledge coefficient measuring local and/or spillover effects from one region to another.

Thus, we are interested in publications that estimate spatial spillover effects using a knowledge production function framework for at least five European countries. Equation 3.1 presents a typical knowledge production function that has been encountered in the literature review:

$$Y_i = \alpha_0 + \beta_1 x_i + \beta_2 (Wx)_j + \sum_{k=1}^{n} \gamma_k \, z_{ki} \, . \qquad (3.1)$$

Y_i is the dependent variable indicating knowledge production (or output) in region *i*, e.g. through number of patents, patents per capita, total factor productivity or wages. x_i and x_j are the knowledge inputs in region *i* and *j* ($i \neq j$), respectively, and comprise of indicators such as R&D employment, R&D expenditures and human capital in form of educated labour. W is a spatial weight matrix. z_{ki} is a vector that measures other covariates in region *i*. α_0 is the intercept coefficient and β_1, β_2 and γ_k are coefficients. The variables Y, x and z can enter the function in log-form depending on whether the structural form is additive by nature or multiplicative, e.g. taking the form of a Cobb-Douglas production function.

The coefficient for β_2 (or β_1) is specified in our empirical model as the dependent variable to make it possible to perform the meta-analysis. Table 3.1 presents other meta-explanatory variables that have been considered when gathering information from the empirical literature on knowledge spillovers in Europe.

Table 3.1 Meta-explanatory variables

1. Time period	7. Estimation method (e.g. OLS, GLS, ML)
2. Time lag between input and output (1, 2,…, years)	8. Number of countries and part of Europe
3. Testing for spatial dependence (e.g. spatial auto-correlation tests)	9. Type of spatial model (spatial lag, spatial error, accessibility, distance band, nearest neighbor)
4. Coverage of economy (services, manufacturing or total etc.)	10. Type of main explanatory variable (R&D and human capital related variables)
5. Type of data (panel, cross-section)	11. Type of geographic unit (NUTS)
6. Initial patent stock	12. Other variables that characterize the publication

Most data for the Y_i variable in the relevant publications has been generated from the European Patent Office and Eurostat in form of annual patent data. However, the focus of the meta-analysis is aimed at the coefficients β_1 and β_2, along with their standard errors. Estimators like these are often characterized either by marginal effects (i.e. additive) or in form of elasticities (i.e. multiplicative).

If the interest is to conduct a meta-analysis on spatial spillover effects, then β_2 is the relevant coefficient, i.e. what influence knowledge input in region *j* has on knowledge output in region *i*. Many publications in our review have not isolated the spillover effect and in this way, it encourages a further gathering of information about β_1 (i.e. the local effect of knowledge input). The majority of publications that fit our requirements have empirically analyzed the effect of β_1 and used various weighting techniques to control for spatial dependence. In order to satisfy the aim of the meta-analysis, β_1 and β_2 are defined in Equations 3.2 and 3.3:

$$\beta_1 = \beta_{Lip^c}, \tag{3.2}$$

$$\beta_2 = \beta_{Sjp^c}, \tag{3.3}$$

$p = (1, 2, \dots, n)$ and $c = (1, 2, \dots, m)$,

where β_{Lip^c} is the local knowledge coefficient in region *i* and β_{Sjp^c} is the spillover knowledge coefficient in region *j*. The subscript term p refers to a specific empirical publication and c is the c^{th} β coefficient in publication p. From now and on we use the terms β_1 and β_2 in our discussion.

3.2 Stylized Facts of the Meta-Sample

Botazzi and Peri (2000) estimate a production function of innovation for European regions using patent and R&D data for the period 1977 to 1995. The main aim of the paper is to analyze the geographical relation between market size and innovative activity. R&D employment and R&D expenditure are used as inputs for both local and spillover knowledge effects.[4] They find that knowledge externalities exist within a geographical area of 200 kilometers, however, decrease fast with an increased distance. Thus, knowledge spillovers are not strong enough to generate sustained growth in the region. One effect that might cause knowledge spillovers in Europe is that regions close to each other use similar technologies.

Crescenzi and Rodrigues-Pose (2008) estimate effects from R&D, knowledge spillovers and proxies for regional innovation systems. 25 EU members are analyzed with the possibility to discriminate between local and non-local knowledge spillovers. Local knowledge effects are measured in terms of R&D expenditure as a share of gross regional product. The knowledge spillover inputs comprise of weighted accessibility to extra-regional innovation. The empirical results show that the complex interaction between local and non-local research shapes the innovation capacity in all regions. Proximity is highly important for knowledge creation, since spillovers are strongly affected when the distance increases.

Krammer (2009) analyses the innovation impact in transition countries, before and after the fall of communism in Eastern European countries. Innovative output, as explained by the number of patents, is estimated by a knowledge production function. Various factors that measure innovative output are considered such as skill of labour, productivity, R&D investment, existing stock of knowledge and other factors that influence knowledge creation in transition countries. Local knowledge effects are estimated in terms of R&D expenditure (total, private and public). The results confirm that universities and the existing knowledge base (in form of private and public R&D) have a crucial impact on augmenting the number of patents as countries go into transition.

The central focus in Maggioni et al (2007) is on geographical and relational spillovers to study the effects of patenting activity in regions within five European countries. They use a gravity model of co-patenting that explains how knowledge flows from inventors in one region to inventors in another region. The model incorporates private and public R&D expenditure in local and non-local regions, technological similarities, geographical distance, common borders etc. Another gravity model is suggested to study the effect of co-patenting in the local region. OLS estimations show that private R&D expenditure induces larger spillover effects from one region

[4] Inputs for spillover knowledge effects are weighted by distance.

to another than public R&D expenditure. Moreover, technological similarities are proven to have a positive effect on co-patenting between two regions.

Moreno et al (2003) and (2005) analyze the spatial distribution of innovative activity and technological spillovers across 138 and 175 regions, respectively, in 17 European countries. Both papers estimate, for different periods, a knowledge production function of innovative activity. Local effects are explained by R&D expenditure as share of GDP, whereas the spillover effects are estimated via contiguity matrices of R&D and weight matrices with neighbor's portion of local R&D up to 750 and 500 kilometers, respectively. In Moreno et al (2003), the results show that spillovers are significant up to a distance of 500 km (i.e. up to a second-order neighborhood). However, in Moreno et al (2005) this relationship is only significant up to a distance of 250 kilometers (i.e. up to a first-order neighborhood). The results from both papers indicate that technological similarities between regions are important for knowledge to spillover.

Pinto and Rodrigues (2010) estimate a knowledge production function to draw conclusions on how regional innovation strategies have affected knowledge creation. 175 European regions are analyzed over the period 1994 to 2001. A model is fitted to explain how local knowledge, measured in terms of patents and high technology patents, is related to local R&D activities. The knowledge production function uses private and public R&D expenditure as a share of regional GDP as input variables for local knowledge effects. The paper concludes that private R&D expenditure is of high relevance to increase the number of patents within a region.

In Greunz (2003) the focus is to study the effects of inter-regional knowledge spillovers across 153 European sub-national regions. A regional knowledge production function is fitted to answer the question whether geographical and technological proximities matter for knowledge creation in Europe. Knowledge spillovers are measured in terms of patents and are explained by a set of local and spillover knowledge inputs. R&D expenditure per capita (total, private and public) enters the function as a local knowledge input. The spillover knowledge variable is represented by R&D expenditure weighted by distance to geographical neighbors. Inter-regional knowledge spillovers seem to exist between regions close to one another and between regions with technological similarities. Moreover, the empirical results show that knowledge spillovers in Europe are mainly driven by private R&D expenditure. However, given that knowledge spillovers exist within a nation, its national borders tend to dampen inter-regional knowledge flows to spread further in Europe.

From 13 publications we have managed to extract local knowledge effects in all publications (110 observations). The local knowledge effect is frequently reported in terms of R&D expenditure. On the other hand, the spillover effect has been far more difficult to interpret due to various methodologies adapted in the empirical regression analyses of these publications. Thus, we have been able to isolate only 75 observations from seven publications. Most commonly, the spillover knowledge effect takes the form of R&D weighted contiguity matrices.

3.3 An Overview of the Publications in the Meta-Sample

Table 3.2 presents an overview of the publications that have been analyzed in the meta-analysis.[5] Each publication displays a certain amount of information that has been gathered in order to generate a data sample. The variables reported include the number of β coefficients (i.e. how many of each β_1 and β_2 there are per publication), what type of local and spillover knowledge variable is utilized, number of countries, time period, geographical unit (i.e. NUTS), dependent variable and the number of observations used in the empirical application.

The local knowledge variable in region *i* is usually reported as R&D employment or R&D expenditure. An important point of discussion regards the large variation in the coefficients for β_1 and β_2. Each publication has a unique approach to measure knowledge production spillovers from a region to another (i.e. the knowledge inputs x_i and x_j differ a lot between publications). While some use the total effect of R&D expenditure to measure spillovers, others apply the variable in per capita or per worker, as private or public expenditure, with natural logarithms or as share of gross domestic product or gross regional product. Thus, we carefully need to evaluate the implications of each specific measure of knowledge production spillovers in order to avoid any misinterpretation of the effect it causes on the dependent variable (i.e. in Y_i).

The second column in Table 3.2 reports the total number of β coefficients per publication.[6] Our total sample of publications that use a quantitative approach is equal to 13.[7] Out of these, we have generated 110 β coefficients for the local knowledge variable in region *i* and 75 β coefficients that measure the spillover of knowledge from region *j*. The number of countries that are analyzed varies from 5 to 25, where most focus is on countries in the EU15. The time period studied differs as well between publications. Some begin as early as the 1970s, while other knowledge production functions are estimated from the mid-1990s and onwards. A number of publications also mix different geographical units. The most common unit varies between NUTS

[5] In order to fit Table 3.2 conveniently to one page, some meta-explanatory variables have been excluded in the presentation of the table. See Appendix for details on the abbreviations in columns three (for β_1) and five (for β_2).

[6] Since most publications run several regression models, the number of β coefficients per publication can exceed 1.

[7] We have reviewed more than 100 publications in total and selected about 40 publications for further analysis. However, the majority of this selection has used irrelevant methods of interpreting the knowledge variable or a quantitative approach not suitable for our purpose, thus narrowing down our sample to 13 publications.

1 (economic country level data) and NUTS 2 (economic region level data). Yearly patent applications and number of patents, in log form, take the form of the dependent variable in the majority of publications (i.e. the Y_i). The number of observations per empirical study (i.e. N) varies a lot from one publication to another. The lowest number of observations is 51 and the highest is 1224.

Table 3.2 Meta-Analysis sample overview

Publication (*p*):	**β_1 coefficient(s) in publication**	**β_1**	**β_2 coefficient(s) in publication**	**β_2**	**European Countries**	**Time period**	**NUTS**	**Dependent variable = Y_i**	**N**
Botazzi and Peri (2000): WP	16	lnRD$_{EMP}$ lnRD$_{EMP/W}$ lnRD$_{EXP}$	16	lnRD$_{EMP}$ lnRD$_{EMP/W}$ lnRD$_{EXP}$ weighted by distance	12	1977-1995	1/2	lnYP$_{APP}$; lnYP$_{APP/W}$	86
Botazzi and Peri (2003): WP	8	lnRD$_{EMP}$ lnRD$_{EXP}$	8	lnRD$_{EMP}$ lnRD$_{SPE}$ weighted by distance	12	1977-1995	0/1/2	lnYP$_{APP}$	86
Crescenzi et al (2007): WP	6	RD$_{EXP\%GRP}$	6	SWANR	8	1990-2002	1/2	lnYP$_{APP}$	97
Crescenzi and Rodriguez-Pose (2008): J	11	RD$_{EXP\%GRP}$	11	AERI TAIPS AIPEA AERI$_{WEI}$	15	1995-2003	1/2	lnGDP$_{CAP}$	166
Hauser et al (2008): J	1	lnRD$_{EXP/W}$	0	N/A	6	Average 97/99/01	1	lnYP$_{APP/C}$	51
Krammer (2009): J	16	lnRD$_{EXP}$ lnRD$_{EXPG}$ lnRD$_{EXPB}$	0	N/A	16	1990-2007	1	PGY	126-221
Maggioni et al (2007): J	4	RD$_{EXPG\%GDP}$ RD$_{EXPB\%GDP}$	0	N/A	5	1995-2001	1/2	P	51
Moreno et al (2003): WP	13	lnRD$_{EXP\%GDP}$	12	lnRD weighted by distance	17	1978-1997	1/2	lnP$_{CAP}$	123
Moreno et al (2005): J	11	lnRD$_{EXP\%GDP}$	9	lnRD weighted by distance	15	1978-2001	0/1/2	lnP$_{CAP}$	175
Pinto (2010): WP	4	RD$_{G\%GDP}$ RD$_{B\%GDP}$	0	N/A	25	1999-2003	1/2	P$_{CAP}$	125
Pinto and Rodrigues (2010): J	4	lnRD$_{EXPG\%GRP}$ lnRD$_{EXPB\%GRP}$	0	N/A	15	1994-2001	2	lnP lnHTP	175
Varga et al (2010): WP	6	lnRD$_{EXP}$	0	N/A	23	2000-2002	1/2	lnP	567
Greunz (2003): J	10	lnRD$_{EXP/C}$ lnRD$_{EXPG/C}$ lnRD$_{EXPB/C}$	13	lnRD$_{EXP}$ lnRD$_{EXPG}$ lnRD$_{EXPB}$ weighted by distance	14	1989-1996	0/1/2	lnP$_{CAP}$	1184-1224
$\sum p$ = 13 Total:	**110**		**75**						

WP = working paper and J = article in journal

Table 3.3 presents the descriptive statistics for the β_1 coefficients obtained from the 13 publications. The table includes the mean value, median, standard deviation from the mean value, as well as the lowest and highest value.

The publications we have analyzed are published in the period 2000 to 2010. They have been published either as working papers (WP) or as articles in journals (J). The number of β_1 coefficients varies per publication, from 1 to 16 coefficients, depending on how many regression models the publication has estimated. The mean value for the local knowledge coefficient is reported between 0.150 and 0.966. The overall mean value of β_1 (i.e. for all 13 publications) is about 0.468, whereas the median is 0.445. The deviation from the mean of β_1 is high for some publications e.g. Crescenzi et al (2007), Maggioni et al (2007) and Pinto and Rodrigues (2010), while it is low for others. The minimum and maximum values for the overall sample of β_1 coefficients are -0.153 and 1.280, respectively.

Table 3.3 Descriptive statistics for β_1

Publication (p)	**β_1 coefficient(s)**	**β_1**				
		Mean	**Standard deviation**	**Median**	**Min**	**Max**
Botazzi and Peri (2000): WP	16	0.966	0.100	0.965	0.830	1.280
Botazzi and Peri (2003): WP	8	0.855	0.065	0.835	0.790	0.960
Crescenzi et al (2007): WP	6	0.369	0.449	0.395	-0.145	0.960
Crescenzi and Rodriguez-Pose (2008): J	11	0.171	0.037	0.166	0.137	0.268
Hauser et al (2008): J	1	0.600	0.000	0.600	0.600	0.600
Krammer (2009): J	16	0.150	0.077	0.141	-0.050	0.274
Maggioni et al (2007): J	4	0.230	0.323	0.235	-0.060	0.510
Moreno et al (2003): WP	13	0.493	0.037	0.485	0.429	0.551
Moreno et al (2005): J	11	0.260	0.022	0.257	0.225	0.294
Pinto (2010): WP	4	0.686	0.443	0.688	0.290	1.080
Pinto and Rodrigues (2010): J	4	0.237	0.346	0.256	-0.153	0.588
Varga et al (2010): WP	6	0.833	0.160	0.780	0.688	1.082
Greunz (2003): J	10	0.320	0.194	0.400	0.030	0.570
$\sum p$ = 13 Overall:	**110**	**0.468**	**0.346**	**0.445**	**-0.153**	**1.280**

WP = working paper and J = article in journal

β_1 = local knowledge coefficient in region i derived from the c^{th} β coefficient in publication p

Table 3.4 reports the descriptive statistics for the knowledge spillovers from region j to region i (β_2). Out of 13 publications, seven report coefficient values for β_2. The mean value for β_2 falls within the range 0.008 and 7.982. The high mean value corresponding to 7.982 is observed in Crescenzi et al (2007). The study uses a spatially weighted average composed by several factors that increases the estimated values of the spillover coefficients, however, excluding it from our sample would imply that we lose valuable information in identifying knowledge spillovers from one region to another. To avoid a misleading interpretation of the overall descriptive statistics of β_2 we also include descriptive statistics that are adjusted for the high values observed in Crescenzi et al (2007) in Table 3.4.

The overall adjusted mean value for the spillover coefficient is 0.106 and the standard deviation is 0.117. The median is close to the mean for all publications, which indicates that each publication has a rather normal distribution in the spillover coefficient. The overall adjusted median equal to 0.052 and a standard deviation of 0.117. The lowest and highest values for β_2 are -0.011 and 0.548, respectively.

Table 3.4 Descriptive statistics for $\boldsymbol{\beta_2}$

Publication (p)	**β_2 coefficient(s)**	**β_2**				
		Mean	**Standard deviation**	**Median**	**Min**	**Max**
Botazzi and Peri (2000): WP	16	0.071	0.027	0.080	0.032	0.110
Botazzi and Peri (2003): WP	8	0.022	0.009	0.027	0.004	0.030
Crescenzi et al (2007): WP	6	7.982	0.466	8.118	7.066	8.311
Crescenzi and Rodriguez-Pose (2008): J	11	0.008	0.008	0.013	-0.008	0.014
Hauser et al (2008): J	0	N/A	N/A	N/A	N/A	N/A
Krammer (2009): J	0	N/A	N/A	N/A	N/A	N/A
Maggioni et al (2007): J	0	N/A	N/A	N/A	N/A	N/A
Moreno et al (2003): WP	12	0.280	0.149	0.268	0.045	0.548
Moreno et al (2005): J	9	0.035	0.023	0.049	-0.011	0.056
Pinto (2010): WP	0	N/A	N/A	N/A	N/A	N/A
Pinto and Rodrigues (2010): J	0	N/A	N/A	N/A	N/A	N/A
Varga et al (2010): WP	0	N/A	N/A	N/A	N/A	N/A
Greunz (2003): J	13	0.169	0.055	0.170	0.040	0.240
$\sum p = 7$ **Overall:**	**75**	**0.736**	**2.157**	**0.080**	**-0.011**	**8.311**
$\sum p = 6$ **Overall adjusted:**	**69**	**0.106**	**0.117**	**0.052**	**-0.011**	**0.548**

WP = working paper and J = article in journal

β_2 = spillover knowledge coefficient in region j derived from the c^{th} β coefficient in publication p

4 Meta-Regression Analysis

4.1 Methodology

A common econometric problem in meta-regression analysis is that observations from the same study can be correlated. Since we have used multiple estimates per study, a static panel data framework called the cluster-specific random effects model (GLS-RE) accounts for the within-study dependence. Previous meta-analyses using this regression technique include Jeppesen et al

(2002), Disidier and Head (2008), and Melo et al (2009). For comparison reasons we have also reported results from a standard OLS model.

4.1.1 Meta-Regression Model

The general model utilized to analyze the local knowledge effects and the spillover of knowledge (i.e. β_Z) in the meta-regressions is as follows: [8]

$$\beta_Z = a_Z + \sum_{d=1}^{24} b_d\, D_d + \varepsilon \qquad Z = 1, 2. \tag{4.1}$$

The dummy variables D_d are defined in Table 4.1. The constant a_Z is equal to the local (β_1) and the spillover effect (β_2), respectively, if b_d and/or D_d is equal to zero for all $d = 1, \dots, 24$. The parameter estimate b_d is zero when the chosen model cannot pick up any variations among observations and studies. The dummy D_d equals zero demonstrates the case chosen as the reference case. The two models for explaining β_Z differ in one aspect. The model explaining variations in local effects does not include the variables about spatial weights (D_8 and D_9), instead the simple dummy for a spatial model (D_7) is used. Obviously, D_7 is excluded in the spillover model because when a spillover effect is estimated, this is done in a spatial model.

Due to a large amount of collinearities among the 24 dummies in Equation 4.1, it is impossible to use all the variables simultaneously. In order to find the final models used in this paper the following strategy was followed:

1. When two variables are collinear, omit the one with the lowest correlation to the β variable and save the other.
2. Continue with step 1 until the multicollinearity problem is sufficiently small.
3. Omit variables with p-value > 0.1.

After fulfilling this strategy, the following two final models were estimated:

$$\beta_1 = a_1 + b_1 D_1 + b_5 D_5 + b_7 D_7 + b_{10} D_{10} + b_{15} D_{15} + b_{22} D_{22} + b_{24} D_{24} \tag{4.2}$$

$$\beta_2 = a_2 + b_1 D_1 + b_3 D_3 + b_8 D_8 + b_{11} D_{11} + b_{15} D_{15} + b_{22} D_{22} + b_{24} D_{24} \tag{4.3}$$

To control for region size we have included a dummy variable (D_{18}) for NUTS in the original model presented in Equation 4.1. However, due to the collinearities with other variables D_{18} is not included in the final two models that we present the results for. In addition, the number of observations per publication (i.e. N) is not included in the meta-regression. The number of observations does not affect the estimated values in the various publications, rather the statistical

[8] Also included in the cluster-specific random-effects model is a study random-effect that controls for study-specific effects that are common to all individual estimates from the same study.

significance. Thus, for the local meta-regression model dummy variable D_{10} is included to capture the statistical significance, whereas D_{11} is included to capture the significance in the spillover meta-regression model. Moreover, three dummy variables that we include in the final two meta-regression models are directly correlated with number of observations. These are the "part of Europe" dummies: D_{14}, D_{15} and D_{16}, where the reference case ($D = 0$) is the publications that include all European regions and thus have consequently the highest number of observations. The part of Europe dummies and the NUTS dummy explain the same information on the number of observations.

Table 4.1 Meta dummy variables

Empirical dimension	Variable	Definition	Reference case, $D = 0$
Working paper or published in a journal	D_1	1 if working paper	Study published in journal
Type of R&D variables	D_2 D_3 D_4 D_5 D_6	1 if R&D per capita 1 if R&D is not in log terms 1 if R&D as a percentage of Gross Regional Product (GRP) 1 if public (government) R&D 1 if business R&D	Study uses log of total R&D expenditure
Spatial model	D_7	1 if inter-regional spillovers are accounted for	Study does not account for spatial spillovers
Spatial weighting regime	D_8 D_9	1 if R&D is weighted by physical distance between regions 1 if R&D in neighboring regions	R&D is weighted by a binary contiguity matrix R&D in non-neighboring regions
Statistical significance	D_{10} D_{11}	1 if p-value of local R&D > 0.05 1 if p-value of spillover R&D > 0.05	Local R&D is significant at the 5% level Spillover R&D is significant at the 5% level
Time structure	D_{12} D_{13}	1 if average year of study period is after 1990 1 if time lag between dependent and independent variables	Average year of study period is before 1990 No time lag between variables is used
Part of Europe (see Appendix for details)	D_{14} D_{15} D_{16}	1 if regions from north, west and south only 1 if regions from west and south only 1 if regions from east only	Study includes countries from all parts of Europe (north, west, south and east)
Type of data	D_{17}	1 if panel data	Study uses cross-sectional data
Level of geographical unit	D_{18}	1 if NUTS 1 regions only	Study includes NUTS 2 regions
Dependent variable	D_{19} D_{20} D_{21} D_{22}	1 if patents are not in log terms 1 if log patents per capita 1 if annual patent growth 1 if annual GRP growth	Study uses log of patent applications as dependent
Education level	D_{23}	1 if there are controls for high education	Study does not control for differences in education level
Initial stock (patents or GRP value)	D_{24}	1 if initial stock is controlled for	Study does not control for initial stock of dependent variable

4.2 Results from the Meta-Regressions

The results of the meta-regressions are presented in Tables 4.2 and 4.3. Let us focus on the results from the random-effects GLS-regression reported in Table 4.2. The reference case ($D_d = 0$) is as follows: If total local R&D expenditure in a region increases by 1%, then the number of patents in the region, on average, increases by 0.482%. If a study uses a spatial model of some kind, i.e. a model that takes into account R&D spillovers from other regions, then the local effect on patent production will be smaller. This is according to the expectations, since if inter-regional R&D effects exist, they probably will have a positive influence local patent production and hence the local effects are exaggerated. Smaller local effects on patent production are also the case for the studies that control for initial patent stock or Gross Regional Product (GRP) value in the region. Moreover, on average, government R&D expenditure has a lower impact on patent production compared to the reference case, which is in line with the stylized facts in section 3.2. In addition, studies conducted on regions in the western or southern part of Europe demonstrate larger local effects from R&D efforts.

To control for possible publication bias we have introduced a dummy variable for whether a study is published or not. The hypothesis is that there is a preference for publishing statistically significant estimates of a positive relationship between R&D expenditure and patent production. If this is true, a published study should on average have a higher β-value. However, the result in Table 4.2 shows the opposite, i.e. a working paper reports, on average, larger local R&D effects.

Table 4.2 Meta regression results: Dependent variable = local effect ($\boldsymbol{\beta_1}$)

Dummy variable		OLS		GLS-RE	
D_1	1 if working paper	0.291 (0.053)	***	0.297 (0.058)	***
D_5	1 if public (government) R&D	-0.235 (0.083)	**	-0.248 (0.099)	**
D_7	1 if inter-regional spillovers are accounted for	-0.165 (0.040)	***	-0.062 (0.023)	***
D_{10}	1 if p-value of local R&D > 0.05	-0.301 (0.056)	***	-0.239 (0.027)	***
D_{15}	1 if regions from west and south only	0.310 (0.063)	***	0.233 (0.072)	***
D_{22}	1 if annual GRP growth as dependent	0.257 (0.062)	***	0.168 (0.051)	***
D_{24}	1 if initial stock (or GRP) is controlled for	-0.170 (0.028)	***	-0.200 (0.034)	***
a_1	Constant	0.523 (0.052)	***	0.482 (0.061)	***
	Number of observations	110		110	
	Number of publications	13		13	
	R^2 (total)	0.795		0.775	
	R^2 (within)			0.367	
	R^2 (between)			0.870	

Note: ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. The standard errors in the parentheses are robust to heteroscedasticity and adjusted for intra-study dependence.

The meta-regression results with the spillover effect as the dependent variable are presented in Table 4.3.[9] In order to check the robustness of the results, two regressions are conducted: one with the full sample (i.e. with seven publications) and one where the outlying observations from Crescenzi et al (2007) were omitted.[10] Given the reference case (D_d = 0): If total local R&D expenditure in a region increases by 1%, then spatial knowledge spillovers, on average, account for an increase in local patent production by 0.066%. Thus, spatial knowledge spillovers seem to have a positive, however, marginal effect on local patent production. In addition, spatial weighting regime seems to matter. If R&D expenditures in other regions are weighted by distance in kilometers or minutes (instead of a binary contiguity matrix) then the spillover effect on average will be larger. Studies conducted on regions in the western or southern part of Europe demonstrate smaller spillover effects from R&D efforts (contrary to the local effects, see Table

[9] Only the GLS-RE results are presented since the results from the OLS estimation were almost identical.

[10] Omitting Crescenzi et al (2007) from the sample group causes D_3 and D_{22} to be highly collinear and no difference is observed any longer between the two dummies. Thus, D_3 is automatically rejected by the GLS-RE estimation.

4.2). If the initial patent stock or GRP value is controlled for, then the region demonstrates higher spillover effects, which is also contrary to the local effects seen in Table 4.2. The other estimates reported Table 4.1 are similar to the ones found for the local effects.

Table 4.3 Meta regression results: Dependent variable = spillover effect (β_2)

Dummy variable		GLS-RE		GLS-RE	
D_1	1 if working paper	0.066 (0.011)	***	0.057 (0.004)	***
D_3	1 if R&D is not in log terms	7.769 (0.026)	***	-	
D_8	1 if R&D is weighted by physical distance between regions	0.093 (0.024)	***	0.090 (0.024)	***
D_{11}	1 if p-value of spillover R&D > 0.05	-0.142 (0.087)	*	-0.074 (0.046)	**
D_{15}	1 if regions from west and south only	-0.114 (0.032)	***	-0.115 (0.033)	***
D_{22}	1 if annual GRP growth as dependent	-7.916 (0.082)	***	-0.204 (0.036)	***
D_{24}	1 if initial stock (or GRP) is controlled for	0.112 (0.032)	***	0.114 (0.030)	***
a_2	Constant	0.079 (0.034)	**	0.066 (0.030)	**
	Number of observations	75		69	
	Number of publications	7		6	
	R^2 (total)	0.997		0.708	
	R^2 (within)	0.175		0.196	
	R^2 (between)	0.999		0.951	

Note: ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. The standard errors in the parentheses are robust to heteroscedasticity and adjusted for intra-study dependence.

5 Conclusions

The purpose of this paper has been to review quantitatively the empirical literature on spatial knowledge spillovers in Europe by means of meta-analysis to determine the extent to which such knowledge spillovers have been empirically documented, as well as the spatial reach of these spillovers. Thoroughly assessed empirical information on these issues is particularly important for the design of policies at the EU, the national and the regional level aimed at increasing knowledge production and economic growth.

The results from our meta-regressions are most interesting in some aspects. However, it is highly important to stress that further research on spatial knowledge spillovers is needed in order to give answers that are more specific on the spatial scope of how knowledge spreads within and between regions in Europe. Hence, there are no previous quantitative studies using meta-regression-analysis with which we can compare our results. The limited research makes it rather difficult to propose a specific policy recommendation to motivate knowledge production and economic growth in Europe. However, three aspects of our results are noteworthy.

First aspect is addressed to the spatial reach of knowledge spillovers. In terms of local European regions, investment in knowledge related activities (e.g. in form of R&D expenditure) tends to augment the local patent production. On the other hand, the analysis shows that the spillovers from R&D investments in non-local regions induce a positive, but marginally small effect on local patent production. Spatial knowledge spillovers tends to be concentrated to regions characterized by same technological attributes and infrastructure development.

Second aspect refers to that total local R&D expenditure is more efficient for local patent production when allocated via private funding networks rather than via public funding streams. University research does not generate as much to patent growth as do private firms. This result might be due to that R&D activities in private firms is monitored more efficiently and knowledge generated is commonly earmarked in terms of patents in order to protect the knowledge discovery for future adaptation. It could also be that a lot of university research spins off to the private industry, which in this way contribute to regional growth through more innovative private firms.

The third aspect is directed to R&D activities that take place in local regions in west and south Europe (comprising of EU12 countries). R&D investments in local regions in west and south Europe induce positive benefits in terms of increasing local knowledge stocks, whereas the effect is the opposite when knowledge spills over from non-local regions. Thus, there is a strong tendency for local knowledge production to be driven by local R&D investments. This result indicates that policies of the Lisbon agenda need to stimulate further innovation, competitiveness and economic growth in all Europe by considering the spatial reach of knowledge spillovers.

A final concluding remark is that the results from our meta-regression-analysis should be treated carefully. Hence, more quantitative studies on spatial knowledge spillovers that use meta-regression techniques are called for in order to make any immersed conclusions on policy recommendations.

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Appendix

Abbreviation of variables in Table 3.2 corresponds to:	
AERI	Accessibility to Extra-Regional Innovation
$AERI_{WEI}$	Weighted Accessibility to Extra-Regional Innovation
AIPEA	Accessibility to Innovation Prone Extra-Regional Areas
GDP_{CAP}	Gross domestic product per capita
HTP	High-technology patents
P	Patents
P_{CAP}	Patents per capita
PGY	Patents granted per year
RD_{EMP}	R&D employment
$RD_{EMP/W}$	R&D employment per worker
RD_{EXP}	R&D expenditure
$RD_{EXP/W}$	R&D expenditure per worker
$RD_{EXP/C}$	R&D expenditure per capita
$RD_{EXP\%GRP}$	R&D expenditure as percentage of gross regional product
$RD_{EXP\%GDP}$	R&D expenditure as percentage of gross domestic product
$RD_{EXPG\%GDP}$	R&D expenditure as percentage of gross domestic product, public
$RD_{EXPB\%GDP}$	R&D expenditure as percentage of gross domestic product, private
RD_{EXPG}	R&D expenditure public
RD_{EXPB}	R&D expenditure business
RD_{SPE}	R&D spending
SWANR	Spatially Weighed Average of Neighboring Regions' R&D
TAIPS	Total Accessibility to Innovation Prone Space
YP_{APP}	Yearly patent applications
$YP_{APP/W}$	Yearly patent applications per worker
$YP_{APP/C}$	Yearly patent applications per capita

Part of Europe (i.e. dummy variables D_{14}, D_{15} and D_{16}) is classified according to:	
North	Sweden, Denmark, Norway and Finland
East	Czech Republic, Slovak Republic, Poland, Hungary, Bulgaria, Estonia, Lithuania, Latvia and Slovenia
West	Germany, France, United Kingdom, Ireland, Belgium, Netherlands and Luxembourg
South	Spain, Portugal, Italy, Cyprus, Malta and Greece
Note: If a part of Europe is referred to within a publication, e.g. North. Then the number of North countries within that publication, may not necessarily correspond to the number of North countries specified in another publication.	