Estimates of the impact of static and dynamic knowledge spillovers on regional factor productivity

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Abstract

We develop an empirical approach to examine static and dynamic knowledge externalities in the context of a regional total factor productivity relationship. Static externalties refer to current period scale or industry-size effects which have been labeled localization externalities or region-size effects known as agglomeration externalities. Dynamic externalities refer to the relationship between *accumulated* or *prior* period knowledge and current levels of innovation, where past learning-by-doing makes innovation positively related to cumulative production over time. Our empirical specification allows for the presence of both static and dynamic externalities, and provides a way to assess the relative magnitude of spillovers associated with spillovers from these two types of knowledge externalities. The magnitude of own-region impacts and other-region (spillovers) can be assessed using scalar summary measures of the own- and cross-partial derivatives from the model. We find evidence supporting the presence of dynamic externalities as well as static, and our estimates suggest that dynamic externalities may have a larger magnitude of impact than static externalities.

JEL Classification: C11, C21, O47, O52, R11

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1 Introduction

The literature on knowledge externalities distinguishes between *static* and *dynamic* externalities as sources of knowledge generation and innovation (Glaeser et al. 1992, Henderson el al. 1995, Krugman and Obstfeld 1997). Static externalities refer to current period scale or industry-size effects which have been labeled localization externalities or region-size effects known as agglomeration externalities. Static externalities associated with localization effects have been labeled Marshall-Arrow-Romer externalities while static externalities associated with agglomeration effects are often called Jacob's externalities. The focus of static externalities is on the relationship between current period regional output and firm-level innovation, which is a positive relationship if we assume that 1) scale effects lead to a greater exchange of knowledge between engineers and scientists and 2) geographical concentration of knowledge workers leads to an increased ability to receive knowledge spillovers. Regions such as Silicon Valley would reflect this idea.

In contrast, dynamic externalities refer to the relationship between *accumulated* or *prior* period knowledge and current levels of innovation. Krugman and Obstfeld (1997) make the argument that accumulation of knowledge or the sum of industry outputs over past periods increase current period firm-level innovation activity. The notion is that past learning-by-doing plays an important role (say in semiconductor production), so that innovation is positively related to cumulative production (of innovative products) over time rather than just current period production.

We focus attention on dynamic externalities which are thought to depend less on geographical connectivity. For example, Echeverri-Carroll and Brennan (1999) rank Texas regions into a hierarchy using knowledge accumulated over time, and show that 'lower ranked' regions (those with less accumulated knowledge) depend on *innovation exchanges* with 'higher ranked' regions (those with more accumulated knowledge). This implies a smaller role played by geography in generation of dynamic externalities than in the case of static externalities. Echeverri-Carroll and Brennan (1999) argue that firms clustered in lower technology regions such as Route 128 (Boston), Research Triangle (Raleigh-Durham) and Austin (Texas) depend on knowledge networks established with firms (and universities, research labs) in Silicon Valley by scientists and engineers working for the firm in order to develop and commercialize new products and processes. In support of this idea, Echeverri-Carroll and Hunnicutt (1998) examined a sample of high technology firms in Texas and conclude that while (static) agglomeration economies seem important to attract high technology firms to a region, (dynamic) externalities were of primary importance, since knowledge used for innovation came mainly from outside regions.

The notion that knowledge capital (accumulated past knowledge) in conjunction with knowledge spillovers represents a source of increased productivity levels (or growth of productivity) has a long history in economics (see, for example, Grossman and Helpman 1994, and Romer 1990). We draw upon this link between productivity and knowledge capital to further explore dynamic externalities in a regional context. Specifically, we quantify the contribution of knowledge capital to total factor productivity (TFP) differences among regions. In doing so the paper lies in the research tradition that finds it congenial and useful to investigate the impact through the lens of the knowledge capital model suggested by Griliches (1979), which augments the production function with the stock of knowledge. This knowledge capital model has remained a cornerstone of the productivity literature for more than 25 years and has been applied in dozens of empirical studies on firm-level productivity and extended to the more aggregated industry- and country-levels (see Griliches 1995 for a survey; and Griffith et al 2004, 2005; Doraszelski and Jammendreu 2008 for recent examples).

We argue that the presence of (static) externalities in conjunction with unobservable/unmeasurable regional knowledge stocks leads to a theoretical implication of spatial dependence in the relationship between regional observations on TFP and knowledge capital (accumulated past knowledge). Similarly, (dynamic) externalities in the presence of common shocks to observed and unobserved knowledge stocks imply a theoretical structure of technological dependence/connectivity between regional observations on TFP and knowledge capital. These theoretical model specifications allow us to formally test for the presence of static and dynamic externalities as well as the relative importance of these two influences on regional TFP. In addition, the structured dependence regression model we employ allows us to quantify spillover/externalities from static and dynamic externalities.

Our empirical results suggest that own-region impacts of knowledge capital on regional TFP are less important than spillover impacts. Further, we find evidence consistent with the findings of Echeverri-Carroll and Hunnicutt (1998) regarding dynamic externalities. These were found to be more important (larger in magnitude) than static externalities.

The remainder of the paper is organized as follows. Section 2 outlines a theoretical framework for assessing the contribution of knowledge capital to regional total factor productivity, when faced with unmeasured/unobservable regional knowledge. We show how unobservable forms of regional knowledge capital in conjunction with observed proxies for regional knowledge capital, lead to a theoretical spatial dependence structure consistent with static externalities. Extending this reasoning using technological connectivity between regions as a proxy for dynamic externalities produces a theoretical model that incorporates spatial as well as technological connectivity structures between regions. Another important methodological contribution discussed in Section 2 is correct assessment of spillover effects, based on an extension of the approach suggested by LeSage and Pace (2009).

Section 3 describes a sample of 198 NUTS-2 regions, representing the 15 pre-2004 EU member states used to empirically implement the model, and provides details on the construction of the total factor productivity and the knowledge (patent) stock measures. Bayesian Markov Chain Monte Carlo estimates and model comparison procedures are used to test for the presence of static and dynamic knowledge externalities. We also present estimates for the relative magnitude of own-region and spillover impacts on regional TFP associated with static and dynamic knowledge externalities.

2 The basic relationship between regional *tfp* and knowledge capital

Static externalities

The case considered here relates to *static externalities* with *dynamic externalities* taken up later in this section. Beginning with a log linear relationship between regional total factor productivity TFP and knowledge stocks K in (1), we explore whether regional differences in the stock of knowledge allows more efficient utilization of capital C and labor L in a constant returns regional production process, $\ln Q = s\ln C + (1-s)\ln L$, where s is the share of capital and $1-s$ that of labor. For a detailed derivation of this relationship from a multi-country Schumpeterian growth model, see Ertur and Koch (2007).

$$\ln TFP = \ln Q - s\ln C - (1-s)\ln L = \beta \ln K + K^{\star} \tag{1}$$

TFP is sometimes referred to as the "Solow residual", since (1) implies that TFP is the difference between (logged) actual/observed output Q and expected or predicted output from a constant returns production process $s\ln C + (1-s)\ln L$. In (1), we relate this residual linearly to (logged) knowledge stocks $\ln K$. Since it is unlikely that empirical measures of knowledge such as K capture the true stock of knowledge available to regions, we posit the existence of unmeasurable knowledge $K^{\star}$ that is included in the (log) linear relationship in (1).

If the unmeasurable/unobservable factors are random, independent, identically distributed (*iid*), these can be viewed as a stochastic disturbance term making the model relationship in (1), amenable to ordinary least-squares regression methods.

It has become a stylized fact that empirical measures of regional knowledge K such as patent applications, educational attainment, expenditures or employment in research and development etc., exhibit spatial dependence (Autant-Bernard 2001, Autant-Bernard and LeSage 2010, Parent and LeSage 2008). That is, a choropleth map of these variables used to proxy regional knowledge would show systematic clustering of high and low values of regional knowledge measures in space.

Spatial dependence in observed measures of regional knowledge K is consistent with static externalities that arise from geographical concentration of knowledge workers that leads to scale effects in firm-level innovation due to greater exchange of knowledge between engineers and scientists clustered in nearby locations. We can formally express spatial clustering by regions of (logged) levels of knowledge stocks $k = \ln K$, using a spatial autoregressive process as shown in (2).

$$
\begin{aligned}
k &= \phi W k + u && (2)\\
u &\sim N(0, \sigma_u^2 I_n) && (3)
\end{aligned}
$$

The n by 1 vector k reflects (logged) cross-sectional observations on regional knowledge stocks in a sample of n regions, and we have introduced a zero mean, constant variance disturbance term u, along with an n by n spatial weight matrix W reflecting the connectivity structure of the regions. The scalar parameter ϕ reflects the strength of spatial dependence in k. The spatial autoregressive process models observed regional knowledge stocks as being related to those of neighboring regions represented by the spatial lag term Wk. If the spatial weight matrix W is row-normalized and consists of equally weighted neighboring observations, then the spatial lag vector Wk represents an average of neighboring regions knowledge stocks. If the scalar dependence parameter ϕ is positive, then knowledge stocks in region i will be positively associated with those of neighboring regions. We note that without loss of generality, we could apply the same reasoning to a sample of firms, so that firm-level knowledge stocks are positively dependent on those of firms located nearby in space.

Substituting the spatial autoregressive specification for observed knowledge stocks in (2) into a logged transformation of our TFP relationship from (1), produced the model in (4), where we use lower-case tfp to denote $\ln TFP$.

$$
\begin{aligned}
tfp &= \beta k + k^{\star}\\
tfp &= \beta(\phi W k + u) + k^{\star}\\
tfp &= \beta \phi W k + (k^{\star} + u) && (4)
\end{aligned}
$$

Expression (4) makes it clear that our specification for the tfp relationship depends on what we assume about the unmeasured/unobservable regional knowledge stocks, denoted by $k^{\star}$. For example, if we assume $k^{\star}$ is *iid* random, then this vector would combine with the *iid* vector u to form an *iid* stochastic disturbance term, making the relationship in (4) amenable to regression methods that assume independence between observations. We don't wish to emphasize (4), since we argue that a random independent specification for $k^\star$ is implausible.

The notion of static externalities suggests that unobservable factors such as $k^\star$ would exhibit spatial dependence. For example, unobservable/unmeasured factors that benefit innovation might be interfirm worker mobility of engineers between nearby regions. The belief that high tech regions have linkages between factors is expressed by Echeverri-Carroll and Brennan (1999), and they note an emerging consensus that knowledge networks play an essentially local role in the innovation process. The belief that geography acts as a boundary on tacit knowledge spillovers among firms in an industry goes back to Marshall (see Henderson 2003). Krugman (1991) (and others) argue that the cost of transmitting knowledge rises with distance, making proximity and location important.

This line of argument motivates use of a spatial autoregressive process specification for $k^\star$, as shown in (5). If we think of k^* as representing say, unobservable contacts between people, then spatial proximity facilitates these.

$$
\begin{aligned}
k^\star &= \psi W k^\star + v && (5)\\
v &= u\gamma + \varepsilon && (6)\\
v &\sim N(0, \sigma_v^2 I_n)\\
\varepsilon &\sim N(0, \sigma_\varepsilon^2 I_n)
\end{aligned}
$$

An important aspect of our specification in (5) is the assumption that shocks or stochastic disturbances v influencing k^* are possibly related to u, shocks to the spatial autoregressive process assigned to govern observed knowledge stocks k. If the scalar parameter $\gamma = 0$, there is no correlation between the shocks u and v, but when $\gamma \neq 0$, we have simple (Pearson) correlation between shocks (u, v) to observed knowledge stocks k and unobserved $k^\star$. Non-zero correlation between (u, v) implies non-zero correlation between k and k^*, so that factors influencing observable knowledge stocks also influence unobservable knowledge stocks. As a concrete example of factors that would lead to correlation between observed and unobserved regional knowledge stocks, consider collaborations between universities and private sector firms located in a region. There would likely be correlation between (unobserved/unmeasured) university research/knowledge that is not patented and observed patents held by firms, if these were a result of collaborative work/arrangements.

Non-zero correlation between k and k^* leads to a very different specification from that shown in (4), where k and k^* were uncorrelated, leading to k^* becoming part of the *iid* disturbance term. If we being with the relationship in (7) and use definitions (2), (5) and (6), we arrive at (8).[1]

[1] See LeSage and Pace (2009) for a more general and detailed exposition of this type of result.

$$
\begin{aligned}
tfp &= \beta k + k^{\star} && (7)\\
tfp &= \psi W tfp + k(\beta+\gamma) + Wk(-\psi\beta - \phi\gamma) + \varepsilon \\
tfp &= \psi W tfp + k\delta_1 + Wk\delta_2 + \varepsilon && (8)
\end{aligned}
$$

The expression in (8) represents what has been labeled a spatial Durbin model (SDM) by Anselin (1988). The SDM model in (8) simplifies to the spatial error model (SEM) shown in (9) when two things hold true, 1) the parameter $\gamma = 0$ indicating no correlation in shocks to measured and unmeasured knowledge, *and* 2) the restriction $\delta_2 = -\psi\beta$ holds true.

$$
\begin{aligned}
tfp &= k\beta + u \\
u &= \psi W u + \varepsilon && (9)
\end{aligned}
$$

We emphasize that the resulting SDM and SEM specifications reflect static knowledge externalities, since these were based on arguments pertaining to geographical proximity. We will derive specifications related to dynamic externalities, but these require a different type of connectivity between regions, that arising from technological networking. This is a subject we take up later.

For the static externalities specifications, a simple likelihood-ratio test of the SEM versus SDM model can be carried out using the log-likelihoods from these two models for any cross-sectional sample of regional data.[2] There are econometric as well as theoretical implications associated with which specification (SDM or SEM) proves most consistent with the sample data.

In terms of econometric implications, the condition $\gamma = 0$ requires that measured knowledge stocks k included in the *tfp* specification are uncorrelated with unmeasured/unobservation knowledge stocks $k^{\star}$. This is an implicit assumption being made by past empirical studies that rely on say patent stocks as a measure/proxy for regional knowledge stocks, and assume any omitted variables are uncorrelated with this included variable, allowing use of independent regression models. In this case, an omitted variable $k^{\star}$ will not produce bias in the model estimate for β, which can be seen from $\delta_1 = \beta + \gamma = \beta$.

A theoretical implication is that the SEM model that arises when $\gamma = 0$ and the additional condition $\delta_2 = -\psi\beta$ holds true, rules out spatial spillovers. In the case of the SEM model, changes in region i capital stock will not exert an impact on region j's *tfp*, that is, $\partial tfp_j/\partial k_i = 0$, as can be

[2]Without loss of generality we could include an intercept term in the model, but ignore this term in our discussion for simplicity.

seen from (9). A related point is that $\gamma \neq 0$ will lead to a rejection of the common factor restriction since the coefficient on k, $(\beta + \gamma)$ will not be equal to that on Wk, $(-\psi\beta - \phi\gamma)$, which rules out the SEM model and spatial spillovers. This suggests that empirical specifications should accommodate situations involving correlated shocks u, v, since these would represent sources of spatial spillovers that have been frequently found by empirical studies. Our specification allows for zero or non-zero correlation between the shocks u, v, with zero correlation arising when the parameter $\gamma = 0$.

Summarizing developments thus far, we have argued that 1) static knowledge externalities should produce spatial dependence in both observed and unobserved measures of regional knowledge stocks, and 2) when observed and unobserved measures of knowledge stocks exhibit correlation (or more generally non-zero covariance), a spatial regression specification (SDM) arises. This specification is consistent with geographically localized interdependent networks of knowledge workers, flows of ideas between nearby regions, and numerous other motivations and phenomena used in the literature to explain the presence of observed spatial/geographically localized knowledge spillovers.

Pursuing the spatial spillovers issue, consider that in the case of the SDM model, $\partial tfp/\partial k$ takes a form that allows changes in region i knowledge stocks, k_i, to impact other-region factor productivity, tfp_j, $j \neq i$. The partial derivatives associated with changes in each region i reflect possible impacts on all other $n-1$ regions. Since we consider changes in each $i = 1, \ldots, n$ region, this results in an n by n matrix expression shown in (10) .

$$\begin{aligned} \partial tfp/\partial k &= (I_n - \psi W)^{-1}(I_n\delta_1 + Wk\delta_2) \qquad (10) \\ \delta_1 &= (\beta + \gamma) \\ \delta_2 &= (-\psi\beta - \phi\gamma) \end{aligned}$$

This important aspect of assessing the impact of spatial spillovers appears to have been overlooked in much of the spatial econometrics literature. Past empirical studies often draw inferences concerning the sign and significance of spatial spillovers based on the parameters ψ, δ_1 and/or δ_2. It should be clear from the partial derivative in (10) that the coefficients δ_1 (and/or δ_2) used in past studies is an incorrect representation of the impact of changes in the variable k on tfp. In fact, the parameter δ_2 can be negative or statistically insignificant when positive and statistically significant spatial spillovers exist based on the correct measure.

LeSage and Pace (2009) have proposed scalar summary measures for the n by n matrix of direct and indirect (spatial spillover) impacts arising from changes in the explanatory variable k on the dependent variable vector representing regional tfp. They point out that the main diagonal of the matrix: $(I_n - \psi W)^{-1}(I_n\delta_1 + Wk\delta_2)$ represents own partial derivatives, which they label direct effects and summarize using an average of these elements of the matrix. The off-diagonal elements correspond to cross-partial derivatives, which can be summarized into scalar measures using the average of the row-sums of the matrix elements excluding the diagonal. In addition to these scalar measures of the direct and indirect effects, LeSage and Pace (2009) provide an approach to calculating measures of dispersion that can be used to draw inferences regarding the statistical significance of the direct and indirect effects, which we rely on here.

Dynamic externalities

In contrast to static knowledge externalities, dynamic externalities result from accumulation of knowledge, and the ability of firms and their workers to establish knowledge networks that link development and commercialization of new products and processes to sources of the accumulated knowledge. As indicated earlier, the ability of firms in lower rank high tech clusters to draw upon cumulated knowledge that frequently resides in the location where it was first developed characterizes dynamic externalities. Links between Silicon Valley, a source of cumulated knowledge and more distant regions such as Austin or Boston are more likely to involve technological rather than geographical proximity. As a concrete example of the difference between static and dynamic knowledge externalities, consider movement of engineering/scientific workers. These workers embody knowledge gained/accumulated from *learning-by-doing*, and movement of such workers across regions represents one way to change knowledge stocks. Movement of knowledge workers is less likely to depend on geographic proximity than on technological proximity between regions. Workers with highly specialized engineering skills are more likely to move to a firm that can use these specialized skills (irrespective of location), making proximity between regions/firms less important than technological proximity/similarity between regions/firms.

There have been a number of challenges to the notion that knowledge externalities are bounded be geographical proximity. Suarez-Villa and Walrod (1997) argue using evidence from a study of electronics firms in the Los Angeles region that firms can safeguard privacy and leap ahead of competitors when they are not located in a cluster of firms engaged in similar activities. Zucker et al. (1998) studying California biotechnology firms argue that exchanges between firms and universities involving star scientists are what leads to positive innovation, not mere spatial proximity or clustering of the firms. As already noted, Echeverri-Carroll and Hunnicutt (1998) argue that for a sample of high technology firms in Texas, knowledge used to produce innovations came mainly from cities outside the region where the firms were located. We use the notion of dynamic externalities here to mean that regions accumulate different levels of knowledge over time, and interregional knowledge spillovers between regions may be more dependent on technological similarity than geographical proximity. Since geographical proximity cannot explain findings of the type mentioned above, technological connectivity between regions seem a likely alternative. Fischer et. al (2006), Parent and LeSage (2008) provide evidence that this type of connectivity is important in studies of patenting activity involving European regions.

We can extend our model to reflect technological networks of connectivity between regions based on an n by n matrix T shown in (11) that measures technological similarity between the n regions in our sample. We will have more to say about how this matrix is constructed when we describe empirical implementation of the model.

The dependence process governing measurable knowledge stocks k now indicates that these depend on "neighboring" regions in technological space rather than conventional "neighbors" in a geographical sense reflected by the spatial weight/connectivity matrix W. Unmeasurable knowledge stocks $k^\star$ available to the regions still exhibit conventional spatial dependence.

$$
\begin{aligned}
k &= \theta T k + u && (11)\\
k^\star &= \psi W k^\star + v && (12)\\
v &= u\gamma + \varepsilon && (13)\\
u &\sim N(0, \sigma_u^2 I_n)\\
v &\sim N(0, \sigma_v^2 I_n)\\
\varepsilon &\sim N(0, \sigma_\varepsilon^2 I_n)
\end{aligned}
$$

Following the same substitutions as before, applied to (14) we arrive at the model in (16).

$$
\begin{aligned}
tfp &= \beta k + k^\star && (14)\\
tfp &= \psi W tfp + k(\beta+\gamma) + Wk(-\psi\beta) + Tk(-\theta\gamma) + \varepsilon && (15)\\
tfp &= \psi W tfp + k\delta_1 + Wk\delta_2 + Tk\delta_3 + \varepsilon && (16)\\
\delta_1 &= (\beta+\gamma)\\
\delta_2 &= (-\psi\beta)\\
\delta_3 &= (-\theta\gamma)
\end{aligned}
$$

There are a number of things to note regarding the extended model in (16). First, if the parameter

$\theta = 0$, so that no technological dependence exists, or $\gamma = 0$ so that no correlation exists between the shocks u, v to the processes governing observed and unobserved knowledge stocks, then $\delta_3 = 0$ and this model collapses to the simpler model from (7). [3] This suggests a simple strategy for testing the presence of technological as well as spatial dependence, based on the $t-$statistic associated with the parameter α_3. As already noted, the case where $\gamma = 0$ is somewhat trivial, so assuming $\gamma \neq 0$, leads to the intuitively appealing result that this represents a test for a lack of technological dependence, ($\theta = 0$) which would result in $\delta_3 = 0$.

Recall that we could consider movement of engineering/scientific workers that embody knowledge gained/accumulated from *learning-by-doing* as a concrete example of why technological connectivity of regions is a way to distinguish between the typical emphasis on spatial/geographical proximity of regions. Movement of knowledge workers is less likely to depend on geographic proximity than on technological proximity between regions. Workers with highly specialized engineering skills are more likely to move to a firm that can use these specialized skills (irrespective of location), making proximity between regions/firms less important than technological proximity/similarity between regions/firms. Autant-Bernard and LeSage (2010) make the point that specialized knowledge may *travel better* (transcend longer distances) because of scientific/engineering networks created by professional organizations, commonalities in university training, etc. The same argument could be made of specialized workers.

In this extended model, the impact of changing k on tfp takes the form:

$$\partial tfp/\partial k = (I_n - \psi W)^{-1}(I_n\delta_1 + Wk\delta_2 + Tk\delta_3) \tag{17}$$

Since the parameter δ_3 is significantly different from zero in our empirical application, we can compare the relative magnitude of impacts from knowledge stocks on total factor productivity that arise from spatial versus technological proximity. Calculation of the scalar summary measures for the own- and cross-partial derivatives proposed by LeSage and Pace (2009) for the model where we restrict $\delta_3 = 0$, versus those from the unrestricted model will allow us to assess the relative importance of the two types of connectivity between regions.

Summarizing these developments, we have argued that 1) static knowledge externalities in the presence of unobservable/unmeasured regional knowledge stocks should produce a spatial regression relationship involving a spatial lag of the dependent and independent variables (and SDM model) in the relation between *tfp* and regional knowledge stocks, and 2) dynamic externalities are less consis-

[3] Strictly speaking, the collapsed model is not equal to (7) in that the parameters of the two models differ. However, we find no statistical evidence to support the parameter restrictions implied by $\gamma = 0$ for our empirical implementation of the model. Further, the simple theoretical development used here is likely to depart from reality, so it seems more plausible to simply treat the model as consisting of parameters $\delta_1, \delta_2, \delta_3$.

tent with spatial dependence than with technological connectivity/similarity between regions. Our empirical specification allows for the presence of both static and dynamic externalities, and provides a way to assess the relative magnitude of spillovers associated with spillovers from these two types of knowledge externalities. The magnitude of own-region (i) and other-region (j) (spillovers) between regions can be assessed using scalar summary measures of the own- and cross-partial derivatives, $\partial tfp_i/\partial k_i$ and $\partial tfp_j/\partial k_i$.

3 An empirical implementation of the model

3.1 The sample data

Our sample is a cross-section of 198 regions representing the 15 pre-2004 EU member states over the 1997-2002 period. The units of observation are the NUTS-2 regions[4] (NUTS revision, 1999, except for Finland revision 2003). These regions, though varying in size, are generally considered to be appropriate spatial units for modeling and analysis purposes. In most cases, they are sufficiently small to capture sub-national variation. But we are aware that NUTS-2 regions are formal rather than functional regions, and their delineation does not represent the boundaries of regional growth processes very well.

The sample regions include regions located in Western Europe covering Austria (nine regions), Belgium (11 regions), Denmark (one region), Finland (four regions), France (20 regions), Germany (40 regions), Greece (11 regions), Ireland (three regions) Italy (20 regions), Luxembourg (one region), the Netherlands (12 regions), Portugal (five regions), Spain (16 regions), Sweden (eight regions) and United Kingdom (37 regions).

Empirical implementation of the two models described in the previous section uses data on total factor productivity and knowledge stocks for each of the n regional economies at six points in time. Total factor productivity calculations at the regional level require interregionally comparable data on regional outputs and inputs. In this study we calculate TFP applying the standard Solowian growth accounting methodology: $\ln Y - \alpha \odot \ln L - (1-\alpha) \odot \ln C$, and use gross value added data in euro (constant prices of 1995, deflated) as measure of output Y. α denotes the $n \times 1$ vector of regional shares in production costs. Following the approach suggested by Hall (1990), α is not calculated as the ratio of total labour compensation to value added (the revenue-based regional factor shares), but

[4]We exclude the Spanish North African territories of Ceuta and Melilla, the Portuguese non-continental territories Azores and Madeira, Corse, the French Départements d'Outre-Mer Guadaloupe, Martinique, French Guayana and Réunion. Two Greek NUTS-2 regions (Ionia Nisia and Voreio Aigaio) that had zero patent stocks were combined with neighbouring NUTS-2 regions to avoid outliers in the spatial and technological lag variables. Since the matrix product Wk, for example, reflects an average of knowledge stocks from geographical neighbors, the introduction of zero values in the vector k will produce aberrant observations in the spatial lag vector Wk.

as cost-based factor shares that are robust in the presence of imperfect factor shares. The symbol $\odot$ denotes the Haddamard (element-by-element) product of the $n \times 1$ vector of shares, and L regional labor and C physical capital.

The data for regional labor come from Cambridge Econometrics. They include only employees, not the self-employed for each region. We adjusted these data on labor inputs to account for differences in average annual hours worked across countries. This is important because average annual hours worked in Swedish manufacturing in the year 1997, for example, were almost 14 percent lower than in Greek manufacturing. Without adjusting for differences in input usage, productivity in Greek and Portuguese regions would be overestimated throughout, while in Swedish and Dutch regions underestimated (Fischer et al. 2009).

Physical capital stock data is not available in the Cambridge Econometrics database, but gross fixed capital formation in current prices is. Thus, the stocks of physical capital were derived for each region i from investment flows, using the perpetual inventory method: $C(t+1) = C(t)(1 - r_C) + I(t+1)$, where $C(t)$ is the stock of physical capital at the end of period t and $I(t+1)$ gross investment during $t+1$. We applied a constant rate r_C of ten percent depreciation (obsolescence) across space and time. The annual flows of fixed investments were deflated by national gross-fixed capital formation deflators. The mean annual rate of growth, which precedes the benchmark year 1997, covers the period 1990-1997 to estimate initial regional physical capital stocks.

Besides the TFP measure, the models also contain a measure of the knowledge capital stock for each of the n regions and the six time periods. We use corporate patent applications[5] to proxy knowledge capital. Corporate patents cover inventions of new and useful processes, machines, manufactures, and compositions of matter. To the extent that patents document inventions, an aggregation of patents is arguably more closely related to a stock of knowledge than is an aggregation of R&D expenditures (Robbins 2006). But use of pattent data has its own caveats, the most glaring being the fact that not all inventions are patented. First, not all inventions meet the patentability criteria set by the EPO, the European Patent Office [the invention has to be novel and non-trivial, and has to have commercial application]. Second, the inventor has to make a strategic decision to patent, as opposed to relying on secrecy or other means of appropriability. See Griliches (1990) and Pavitt (1985) for a general discussion about the limits and the opportunities of patents as economic indicators. All of these issues provide a motivation for our approach that posits latent unobservable knowledge stocks.

Patent stocks were derived from European Patent Office (EPO) documents. Each EPO document

[5] Common practice is to use R&D expenditures as a measure of knowledge capital. One problem with this measure is some double counting that occurs because R&D labor and capital are counted twice, once in the available measures of physical capital and labor, and again in the measure of R&D capital stocks (see Griliches and Mairesse 1984). By using patents we avoid this problem. But patents have their own well-known weaknesses.

provides information on the inventor(s), his or her name and address, the company or institution to which property rights have been assigned, citations to previous patents, and a description of the device or process. To create the patent stocks for 1997-2002, the EPO patents with an application date 1990-2002 were transformed from individual patents into stocks by first sorting based on the year that a patent was applied for, and second the region where the inventor resides. In the case of cross-region inventor teams we used the procedure of fractional rather than full counting. Then for each region i, patent stocks were derived from the patent data, using the perpetual inventory method: $K(t+1) = K(t)(1-r_K) + S(t+1)$, where $K(t)$ is the patent stock at the end of period t, $S(t+1)$ are knowledge production activities during $(t+1)$, measured in terms of corporate patent applications, and r_K is a constant depreciation rate. Because of evident complications in tracking obsolescence over time, we used a constant depreciation rate $r_K = 12$ that corresponds to the rate of knowledge obsolescence in the US as found in Caballero and Jaffe (1993) for the year 1990. Patent stocks were initialized the same way as physical capital.

3.2 Estimates and tests of the model assumptions

For presentation purposes we will label two models as shown in (18) and (19), where we have added an intercept term α_0 and associated n by 1 vector of ones, ι_n to the model to reflect the non-zero mean of the dependent variable tfp.

$$\text{Static externalities model:} \quad tfp = \alpha_0\iota_n + \psi W tfp + \delta_1 k + \delta_2 W k + \varepsilon \tag{18}$$

$$\text{Dynamic externalities model:} \quad tfp = \alpha_0\iota_n + \psi W tfp + \delta_1 k + \delta_2 W k + \delta_3 T k + \varepsilon \tag{19}$$

We note that our labeling for the model in (19) might be perceived as a bit of a misnomer, since this model includes both conventional static knowledge externalities due to the presence of the geographical connectivity matrix W, as well as allowing for dynamic knowledge externalities arising from technological connectivity of regions represented by the matrix T. However, we treat technological connectivity as a nested concept. Given the preponderance of empirical evidence in favor of the presence of spatial dependence (geographical/static spillovers/externalities) an omitted variables objection could be raised against a specification that excluded the matrix W in favor of a matrix T alone. Our treatment tests for evidence in favor of dynamic externalities while conditioning on static externalities. More detailed sample data information would likely be necessary to separately identify and quantify the impact of these two types of externalities, perhaps establishment-level information on a sample of individual firms located at various points in space. Our statistical tests for the presence of dynamic knowledge spillovers focuses on whether the augmented model containing technological connectivity produces significantly different spillovers from the simpler model based only on spatial connectivity.

Pooled versions of the models were used because estimates based on a cross-sectional sample for each of the six years produced estimates that were within one standard deviation of each other. These estimates along with an average standard deviation are reported in Table 1. Pooling over the M time periods involves forming a vector $\widetilde{tfp} = vec(tfp_1, \; ..., tfp_M)$, where the *vec* operator stacks the $n \times 1$ column vectors tfp_m, $(m = 1, \ldots, M)$ to create an $Mn \times 1$ vector for the dependent variable. Similarly, we can form: $\tilde{k} = vec(k_1, \ldots, k_M)$. The spatial weight matrix W does not change over time, so we can form $\tilde{W} = I_M \otimes W$ to implement the pooled models.

Table 1 about here

The $n \times n$ technological weight matrix T in the model labeled *Dynamic externalities model* from (19) measures the closeness of regional economies in a technological space spanned by 120 distinct technology fields, described by 120 patent classes of the International Patent Code (IPC) classification[6]. We utilized EPO corporate patents with an application date in the period 1990 to 1995 to define the technological position of a region, based on a 120-by-1 vector containing the share of patents filed in each of the six years in the IPC categories. This definition reflects the region's diversity of inventive activities of its firms. Following Jaffe (1986), a Pearson correlation coefficient was used to measure the technological proximity between any two regions of the sample. A high correlation indicates similarity and a low correlation dissimilarity. The matrices $T_m (m = 1, \ldots, M)$ were formed for each of the $M = 6$ years by finding the r regions that exhibited the highest correlation coefficients with each region. A single value of r was used, but separate matrices form the pooled weight matrix $\tilde{T} = diag(T_1, \ldots, T_M)$ based on the IPC category patenting activities in each of the $M = 6$ years. This allows us to express the pooled models in an identical format as in the *Dynamic externalities model* from (19) by replacing the $n \times 1$ vectors, $tfp, \; k, \; Wk, \; Tk$ with stacked vectors $\widetilde{tfp}, \; \tilde{k}, \; \widetilde{Wk}$ and $\widetilde{Tk}$.

Table 2 about here

Bayesian model comparison methods were used to calculate posterior model probabilities based on the log-marginal likelihood for pooled models with varying numbers r of technological neighbors

[6]These patent classes refer to the second level of the IPC classification system that is used to classify inventions claimed in the EPO patent documents.

and spatial neighbors s, based on nearest neighboring regions in technological and geographical space respectively. The log-marginal likelihoods and posterior model probabilities reported in Table 2 are based on LeSage and Parent (2007). Since these models all contain the same number of parameters, non-informative priors were used[7]. The posterior model probabilities in Table 2 used models based on spatial weight matrices containing $s = 5$ to $s = 9$ nearest neighbors, and technological weight matrices constructed using $r = 2$ to $r = 10$ nearest technological neighbors. Estimates of spillover impacts arising from changes in regional knowledge stocks are dependent on the specification of the spatial and technological weight matrices W and T, as can be seen from the partial derivative in (17). This motivated Bayesian model comparison of alternative matrices W and T. The posterior model probabilities point to eight nearest technological neighbors and indicate seven spatial neighbors. Empirical results reported in the remainder of the paper were based on $s = 7$ and $r = 8$.

Table 3 about here

Pooled estimates for the *Static* and *Dynamic* models in (18) and (19) are presented in Table 3. These are Bayesian MCMC estimates based on non-informative priors, which were nearly identical to maximum likelihood estimates. We relied on MCMC estimation to produce a sequence of 5,000 retained draws that could be used to construct the measures of dispersion for the effects estimates discussed in the next section. It is important to keep in mind that the parameter estimates for δ_2 and δ_3 do not represent the impact of spatial spillovers arising from regional knowledge stocks. To accurately assess the magnitude of spatial spillovers we will rely on the scalar summary measures that represent $\partial tfp/\partial k$ discussed in Section 2. This topic will be taken up in Section 3.3.

One point of interest is whether excluded variables reflecting unobserved or unobservable knowledge capital are correlated with the included knowledge stock measure k. This can be formally tested by examining the restriction $-\psi\delta_1 = \delta_2$ from (18). If this restriction holds, then the SEM model is appropriate and the shocks to observed and unobserved knowledge stocks are uncorrelated. From the posterior mean estimates for the *Static externalities model* in Table 3, we see that $-\psi\delta_1 = -0.0689$ with a lower 99% interval of -0.0460 and $\delta_2 = -0.0137$, so we can conclude this restriction is not consistent with the estimates. This suggests the presence of unobserved regional knowledge stocks.

A likelihood ratio test statistic can be constructed using twice the difference in log-likelihood function values from the SDM and SEM models, which is chi-squared distributed with one degree of freedom reflecting the single restriction. These two log-likelihood values were -159.4, and -181.0, respectively, producing a chi-squared statistic equal to 43.2. Since the 99% critical value for a chi-

[7]See LeSage (1997) regarding Bayesian MCMC estimation of these models.

squared deviate with one degree of freedom is 6.315, we can reject the restriction as being consistent with the sample data. Of note, the log-likelihood function value for the *Dynamic externalities model* equalled -143.3, which is significantly different from that for the *Static externalities model*, when subjected to a likelihood ratio test based on the restriction implied by these nested models. This of course suggests evidence in favor of the presence of dynamic knowledge externalities in our sample data.

A second issue is whether the (pooled) knowledge stock variable $\tilde{k}$ exhibits spatial dependence, an assumption we made in deriving the *Static externalities model*. Using the spatial regression model: $\tilde{k} = \alpha_0 + \theta(I_M \otimes W)\tilde{k} + \varepsilon$, we find a maximum likelihood estimate $\hat{\theta} = 0.7249$ and an asymptotic t-statistic equal to 33.4, allowing us to conclude that observed (log) knowledge stocks at the regional level exhibit strong spatial dependence. This result is consistent with numerous other findings from the literature.

For the extended *Dynamic externalities model*, we tested whether (pooled) knowledge stocks $\tilde{k}$ exhibit technological dependence, using $\tilde{k} = \alpha_0 + \varphi \widetilde{Tk} + \varepsilon$. The parameter estimate for φ is 0.6869 with a $t-$statistic of 17.9, so we conclude that the assumptions made in constructing the *Dynamic externalities model* appear consistent with the sample data used here.

3.3 Spillover impacts from knowledge capital on total factor productivity

As indicated in Section 2, it is necessary to properly calculate the direct, indirect and total effects associated with changes in knowledge stocks on total factor productivity in our spatial regression framework. For the *Static externalities model* the direct and spillover effects reflect an average of diagonal and off-diagonal elements of: $\partial tfp/\partial k = [I_M \otimes I_n - \hat{\psi}(I_M \otimes W)]^{-1}[(I_M \otimes I_n)\hat{\delta_1} + (I_M \otimes W)\hat{\delta_2}]$ which correspond to scalar summary measures of the own and cross-partial derivatives. The set of 5,000 retained MCMC draws from estimation were used to construct upper and lower 99% credible intervals for these effects estimates, allowing us to test for their statistical significance.

Table 4 about here

Table 4 shows the posterior mean effects estimates along with 99% credible intervals, which indicate that the direct, indirect and total effects for the two models are positive and different from zero based on the credible intervals. The indirect effects reported in the table are formal measures for the magnitude of knowledge externalities from the *Static externalities model*. We emphasize that it would be a mistake to interpret the coefficient estimate $\hat{\delta_2}$ as representing spatial spillover magnitudes in spatial regression models that involve spatial lags of the dependent variable. To see how inaccurate this is, consider the difference between the coefficient estimates for δ_2 in Table 3 and the true indirect effects correctly calculated from the partial derivatives of the spatial regression model. Using the *Static externalities model* as an example we see that $\hat{\delta_2}$ is not statistically significantly different from zero, whereas the true indirect effect estimate is 0.1631 in Table 4, with a lower 0.01 bound of 0.0729 making it clearly a positive and significant effect.

The *Dynamic externalities model.* allows for both spatial/static as well as dynamic/technological knowledge spillover, and produces the largest indirect/spillover effects, based on $\partial tfp/\partial k = [I_M \otimes I_n - \hat{\psi}(I_M \otimes W)]^{-1}[(I_M \otimes I_n)\hat{\delta_1} + (I_M \otimes W)\hat{\delta_2} + \mathrm{diag}(T_1, \ldots, T_M)\hat{\delta_3}]$.

The interpretation of these partial derivative effects estimates is that changes in knowledge stocks would lead to a move from one steady-state equilibrium to a new steady-state (see LeSage and Pace 2009). The effects estimates in Table 4 reflect the cumulative impact of knowledge stock changes that would arise in the movement between equilibrium steady-states. Since we have a cross-sectional model, there is no information regarding the time required for the move between steady-states. Given the log-transformation of both the dependent and independent variables in our models, the effects estimates have an elasticity interpretation. For the *Static externalities model*, a 10% increase in regional patent stocks is associated with a 2.7% increase in factor productivity, composed of a 1.1% direct effect and 1.6% spillover effect. For the *Dynamic externalities model*, a 10% increase in regional patent stocks would lead to a 3.7% increase in factor productivity in the new steady-state equilibrium. Of this, 2.7% represents spillover effects and less than one percent a direct effect.

Table 5 about here

To better understand the scalar summary measures of cumulative direct, indirect and total effects over space reported in Table 4, we can carry out a spatial decomposition of the effects estimates following LeSage and Pace (2009). This is based on the profile of marginal indirect effects associated with each order of the matrix W. Note that we can rely on the asymptotic expansion: $[I_M \otimes I_n - \hat{\psi}(I_M \otimes W)]^{-1} = I_M \otimes I_n + \hat{\psi}\tilde{W} + \hat{\psi}^2\tilde{W}^2 + \hat{\psi}^3\tilde{W}^3 \ldots$ to produce effects estimates for first-order neighbors ($\tilde{W}$), second-order neighbors, ($\tilde{W}^2$), third-order neighbors ($\tilde{W}^3$), etc., which is how the marginal indirect effects associated with each order of the matrix $\tilde{W}^q$ ($q = 1, \ldots, 10$) were produced. Table 5 shows the marginal indirect effects, which were cumulated (to order q=100) to produce the numbers reported in Table 4. The table also reports lower and upper 99% credible intervals constructed from the 5,000 retained MCMC draws, allowing us to pass judgement on the statistical significance of the marginal effects estimates.

From the table, we see that the indirect (spillover) effects from the *Static externalities model* are significantly different from zero beginning with the first-order neighbors where $\tilde{W}^q = \tilde{W}$. They decay to less than one-half of the $q = 2$ magnitude by $q = 4$. There are seven first-order neighbors, and the average number of second-order neighbors in $\tilde{W}^2$ equals 18, whereas the average number of third-order neighbors in $\tilde{W}^3$ is 30. The spillover impacts decline rapidly as we move to regions that are 'neighbors to the first-order neighbors' ($\tilde{W}^2$), and 'neighbors to the neighbors of the first-order neighbors' ($\tilde{W}^3$), etc., which seems to indicate geographic localization of the productivity effects arising from static knowledge externalities. From the table we see that indirect effects from the *Static externalities model* are still positive and significantly different from zero for $\tilde{W}^{10}$, which encompasses around 130 regions on average for our sample. However, given our elasticity interpretation of the impacts, the effects for tenth-order neighbors equal to 0.0029 are not likely to be of economic significance in terms of their impact on total factor productivity.

The *Dynamic externalities model* indirect effects or knowledge externalities/spillovers show a large and significant impact when $q = 2$, and as in the case of externalities from the *Static externalities model*, there is a rapid decay as we move to higher-order neighbors. For $q = 4$, the effects are less than one-half of those for $q = 2$.

The direct effect magnitudes are not presented in Table 5 because they die down very quickly to zero. Since these reflect the main diagonal elements of the matrix measuring $\partial tfp/\partial k$, we note that although the spatial weight matrix W contains zeros on the main diagonal, the matrices $W^2, W^3, \ldots$ do not have zero diagonals. This is because a region is a second-order neighbor to itself, which has the implication that even the 'direct effect' estimates reflect some spatial feedback in any model that contains spatial lags of the dependent variable. Despite this, the amount of feedback is small for our sample data, as can be seen by the closeness of the direct effect estimates for the two models reported in Table 4 and the parameter estimates for δ_1 in Table 3. For example, in the case of the *Static externalities model*, the coefficient estimate for δ_1 is equal to 0.1029 and the direct effect estimate in Table 4 equals 0.1106, with the small difference between these two magnitudes reflecting feedback effects from neighbors. Similarly, we see small magnitudes separating the estimates for δ_1 from the *Dynamic externalities model* in Table 3 and the direct effects estimates reported in Table 4, suggesting very little feedback effect.

Having explained issues related to interpreting the direct, indirect and total effects estimates, we can consider the magnitudes of these estimates from the two models shown in Table 4. The indirect effects or cross-region knowledge spillovers from the *Static externalities model* are around 1.5 times the direct effects. In contrast, spillovers from the *Dynamic externalities model* that includes technological connectivity between regions increases the spillover (indirect effects) estimates to nearly triple that of the direct effects. Comparing static to dynamic knowledge spillovers based on models from (18) and (19), we see almost a doubling in the size of dynamic versus static spillovers (0.27 versus 0.16). The dynamic externalities appear significantly larger than the static, since the mean for the indirect effects from the *Dynamic externalities model* fall outside the 95% interval for the *Static externalities model* indirect effects. From this, we conclude that both static as well as dynamic externalities are at work to produce knowledge spillovers in the case of regional total factor productivity.

Our empirical results suggest that both static and dynamic externalities play a role, with a larger role for dynamic than static, consistent with results found by Echeverri-Carroll and Brennan (1999). Specifically, we find static spillovers (on average, cumulated over all regions) having a magnitude of 1.5 times the direct/own-region impact for a total impact of 2.5, whereas static plus dynamic spillovers (on average, cumulated over all regions) have three times the spillover impact leading to a total impact of four.

A policy implication is that setting spatial spillovers to zero (as is done in ordinary regression models) would lead to a four-fold underestimate (25 percent of the true value) of positive knowledge spillovers that accrue when cumulating over all other regions. This would of course severely bias any cost/benefit study of programs that target or promote regional knowledge capital accumulation. Further, ignoring/excluding technological dependence (through the use of a spatial/static externalities model alone) would also lead to a less severe (62.5 percent of the true value) underestimate of positive spillover benefits by ignoring dynamic externalities.

Programs that target specific regions will benefit neighboring regions by creating static knowledge externalities and the (cumulative) magnitude of these benefits can be estimated. In addition, we show how a profile of decay in knowledge externalities across neighboring regions (which we label 'marginal effects') can be estimated. We note that if interest is on knowledge spillovers for a specific region, the methods described here can be used to produce measurements/estimates for specific regions rather than the scalar summary average over the entire sample. This would involve use of a single row from the matrix of partial derivatives shown in (17). The main diagonal (row) element from this row measures the direct effect whereas the sum of off-diagonal (row) elements reflects spillovers to other regions (see LeSage and Pace 2009 for additional details). Here again, the spatial profile of benefits falling on individual neighboring regions could be calculated using the same approach as illustrated in Table 5.

4 Conclusions

Despite the possible measurement difficulties and reservations with our simple reduced-form regression model framework for assessing the contribution of static and dynamic knowledge externalities to total factor productivity, our study has produced a number of interesting empirical results. *First*, evidence suggests that regional total factor productivity depends on its own knowledge capital (direct impact), as well as that of other nearby regions (static externalities). *Second*, direct impacts are important, but externalities or knowledge spillover effects are more important. In fact, external effects are three times the magnitude of the direct effects. *Third*, while the beneficial productivity effects from geographically neighboring knowledge stocks (static externalities) have been established in earlier empirical literature (see Smith 1999, Robbins 2006, Fischer et al. 2009), evidence for the importance of the technological dimension which we attribute to the notion of dynamic externalities that has been introduced in the literature is new. *Finally*, empirical evidence that dynamic externalities may have a larger magnitude of impact than static externalities is also new.

Diffusion of knowledge takes time, sometimes a considerable period of time. The price paid for the simplicity of our framework is abstraction from any explicit time lag structure for the effects of knowledge capital on regional total factor productivity. Further explorations with disaggregated data and an explicit treatment of the dynamics involved using a space-time panel data methodology to explore the knowledge-productivity nexus would undoubtedly provide additional insights.

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References

Anselin, L. (1988): *Spatial Econometrics: Methods and Models*, Dordrecht: Kluwer Academic Publishers.

Autant-Bernard C. (2001): The geography of knowledge spillovers and technological proximity, Economics of Innovation and New Technology 10(4): 237-254

Autant-Bernard C. and LeSage, J.P. (2010): Quantifying Knowledge Spillovers using Spatial Econometric Models, (forthcoming in) Journal of Regional Science.

Caballero J.R. and Jaffe J.B. (1993): How high are the giants shoulders: An empirical assessment of knowledge spillovers and creative destruction in a model of economic growth. In Blanchard U. and Fischer S. (eds.) NBER Macroeconomics Annual 1993, Vol. 8, Cambridge [MA]: The MIT Press, pp. 15-74

Doraszelski U. and Jammandreu J. (2008): R&D and productivity: Estimating production functions when productivity is endogenous. Discussion paper no. 6636, Centre for Economic Policy Research, London

Echeverri-Carroll E.L. and Brennan W. (1999): Are innovation networks bounded by proximity? in *Innovation, networks and localities* Manfred M. Fischer, Luis Suarez-Villa, Michael Steiner (eds.), Berlin: Springer, pp. 28-48.

Echeverri-Carroll E.L., Hunnicutt L. and Hansen N. (1998): Do assymmetric networks help or hinder small firm's ability to export? Regional Studies (13): 721-733

Ertur, C. and Koch W. (2007): Growth, technological interdependence and spatial externalities: theory and evidence. Journal of Applied Econometrics 22(6): 1033-1062

Fischer M.M., Scherngell, T. and Jansenberger, E. (2006): The geography of knowledge spillovers between high-technology firms in Europe: Evidence from a spatial interaction modelling perspective. Geographical Analysis 38 (3): 288-309

Fischer M.M., Scherngell T. and Reismann M. (2009): Knowledge spillovers and total factor productivity. Evidence using a spatial panel data model. Geographical Analysis 41(2): 204-220

Glaeser, E., Kallal, H., Scheinkman, J. and Shleifer A. (1992): Growth in cities, *Journal of Political Economy*, 100, 11261152.

Griffith R., Harrison R. and van Reenen J. (2005): How special is the special relationship? Using the impact of U.S. R&D spillovers on U.K. firms as a test of technological sourcing. American Economic Review 96(5): 1859-1875

Griffith R., Redding S. and van Reenen J. (2004): Mapping the two faces of R&D: Productivity growth in a panel of OECD countries. The Review of Economics and Statistics 86(4): 883-895

Griliches Z. (1979): Issues in assessing the contribution of research and development to productivity growth. The Bell Journal of Economics 10(1): 92-116

Griliches Z. (1990): Patent statistics as economic indicators: A survey. Journal of Economic Literature 28(4): 1661-1707.

Griliches Z. (1995): R&D and productivity: Econometric results and measurement issues. In Stoneman P. (ed) Handbook of the economics of innovation and technological change. Oxford [UK] and Cambridge [MA], Basil Blackwell, pp. 52-89

Griliches Z. and Mairesse J. (1984): Productivity and R&D at the firm level. In Griliches Z. (ed) R&D, patents and productivity. The University of Chicago Press, Chicago and London, pp. 339-374

Grossman G. and Helpman E. (1994): Endogenous innovation in the theory of growth. Journal of Economic Perspectives 8(1): 23-44

Hall R.E.C. (1990): Invariance properties of Solow's productivity residual. In Diamond P (ed) Growth/productivity/employment. The MIT Press, Cambridge [MA], pp. 71-112

Henderson, V., A. Kuncoro and M. Turner (1995). Industrial development in cities, *Journal of Political Economy* 103(5): 1067-1090.

Henderson, V. (2003): Marshall's scale economies, *Journal of Urban Economics* 53(1): 1-28.

Jaffe A.B. (1986): Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits and market value. American Economic Review 76: 984-1001

Krugman, P. (1991): Increasing returns and economic geography. Journal of Political Economy 99: 483-99

Krugman, P. and Obstfeld M. (1997): *International Economics: Theory and practice.* New York, Addison-Wesley.

LeSage J.P. (1997): Bayesian estimation of spatial autoregressive models. International Regional Science Review 20(1/2): 113-129

LeSage J.P. and Pace R.K. (2009): Introduction to spatial econometrics. Boca Raton, London and New York, CRC Press (Taylor & Francis Group)

LeSage J.P. and Parent O. (2007): Bayesian model averaging for spatial econometric models, Geographical Analysis 39(3): 241-267

Parent O. and LeSage J.P. (2008): Using the variance structure of the conditional autoregressive spatial specification to model knowledge spillovers. Journal of Applied Econometrics 23(2): 235-256

Pavitt K. (1985): Patent statistics as indicators of innovative activities: Possibilities and problems. Scientometrics 7: 77-99.

Robbins C.A. (2006): The impact of gravity-weighted knowledge spillovers on productivity in manufacturing. Journal of Technology Transfer 31(1): 45-60

Romer P. (1990): Endogenous technological change. Journal of Political Economy 98(5) Part 2: The problem of development: A Conference of the Institute for the Study of Free Enterprise Systems: S71-S102

Smith P.J. (1999): Do knowledge spillovers contribute to U.S. state output and growth? Journal of Urban Economics 45(2): 331-353

Suarez-Villa, L. and Walrod, W. (1997): Operational Strategy, R&D, and Intra-metropolitan Clustering in a Polycentric Structure: The Advanced Electronics Industries of the Los Angeles Basin. Urban Studies 34(9): 1343-1380

Zucker, L.G., Darby, M.R. and Brewer, M.B. (1998): Intellectual human capital and the birth of US biotechnology enterprises. American Economic Review 88: 290-306

Table 1: Annual Model Estimates[†]

Variable	1997	1998	1999	2000	2001	2002	Pooled	Standard deviation
k	0.0658	0.0745	0.0799	0.0925	0.1010	0.0981	0.0853	0.0252
Wk	-0.0200	-0.0161	-0.0152	-0.0105	-0.0157	-0.0114	-0.0148	0.0306
Tk	0.1087	0.0860	0.0721	0.0580	0.0539	0.0455	0.0707	0.0376
$Wtfp$	0.7229	0.7022	0.6783	0.0642	0.6395	0.6293	0.6691	0.0712

[†] These estimates are based on seven nearest spatial neighbors and eight technological neighbors. Determination of the number of neighbors is described in the running text.

Table 2: Posterior model probabilities for numbers of spatial and technological neighbors

	# spatial neighbors				
# technological neighbors	s=5	s=6	s=7	s=8	s=9
r=2	0.0000	0.0000	0.0000	0.0000	0.0000
r=3	0.0000	0.0000	0.0001	0.0000	0.0000
r=4	0.0000	0.0000	0.0006	0.0000	0.0000
r=5	0.0000	0.0000	0.0162	0.0000	0.0000
r=6	0.0000	0.0000	0.0128	0.0000	0.0000
r=7	0.0000	0.0000	0.2102	0.0000	0.0000
r=8	0.0000	0.0000	0.4775	0.0001	0.0000
r=9	0.0000	0.0000	0.1808	0.0001	0.0000
r=10	0.0000	0.0000	0.1013	0.0001	0.0000

Table 3: Estimates for static and dynamic externalities models pooled over 1997 to 2002

Static: $tfp = \alpha_0 + \psi Wtfp + \delta_1 k + \delta_2 Wk + \varepsilon$			
Posterior estimates	Lower 0.01	Mean	Upper 0.01
α_0	0.3328	0.5086	0.6799
ψ	0.6020	0.6698	0.7340
δ_1	0.0818	0.1029	0.1241
δ_2	-0.0460	-0.0137	0.0183
σ_ε^2	0.1266	0.1411	0.1572
Dynamic: $tfp = \alpha_0 + \psi Wtfp + \delta_1 k + \delta_2 Wk + \delta_3 Tk + \varepsilon$			
Posterior estimates	Lower 0.01	Mean	Upper 0.01
α_0	-0.0419	0.1886	0.4025
ψ	0.5990	0.6627	0.7230
δ_1	0.0621	0.0843	0.1070
δ_2	-0.0461	-0.0131	0.0180
δ_3	0.0377	0.0704	0.1029
σ_ε^2	0.1234	0.1376	0.1536

Table 4: Cumulative direct, indirect and total impact estimates

	0.01 level	Mean	0.99 level
Static knowledge spillovers model			
Direct effect of knowledge capital	0.0898	0.1106	0.1318
Static spillover effects from knowledge capital	0.0730	0.1631	0.2681
Total effects of knowledge capital	0.1787	0.2738	0.3803
Dynamic knowledge spillovers model			
Direct effect of knowledge capital	0.0643	0.0930	0.1204
Dynamic spillover effects from knowledge capital	0.1856	0.2777	0.3928
Total effects of knowledge capital	0.2540	0.3708	0.5107

Table 5: Marginal knowledge spillover and total impact estimates: (a) *Static* and (b) *Dynamic*

	Static knowledge externalities						
W^q	Spillover effects				Total effects		
	Lower 0.01	Mean	Upper 0.99		Lower 0.01	Mean	Upper 0.99
q=1	0.0000	0.0000	0.0000		0.0806	0.1024	0.1240
q=2	0.0434	0.0598	0.0769		0.0434	0.0598	0.0769
q=3	0.0231	0.0354	0.0493		0.0269	0.0402	0.0551
q=4	0.0166	0.0259	0.0375		0.0177	0.0276	0.0399
q=5	0.0106	0.0179	0.0279		0.0113	0.0190	0.0296
q=6	0.0068	0.0125	0.0207		0.0072	0.0131	0.0219
q=7	0.0044	0.0087	0.0157		0.0046	0.0091	0.0164
q=8	0.0027	0.0060	0.0116		0.0029	0.0063	0.0121
q=9	0.0017	0.0042	0.0087		0.0018	0.0043	0.0091
q=10	0.0011	0.0029	0.0065		0.0011	0.0030	0.0067
	Dynamic knowledge externalities						
W^q	Spillover effects				Total effects		
	Lower 0.01	Mean	Upper 0.99		Lower 0.01	Mean	Upper 0.99
q=1	0.0000	0.0000	0.0000		0.0621	0.0847	0.1067
q=2	0.0714	0.0944	0.1183		0.0714	0.0944	0.1183
q=3	0.0421	0.0597	0.0796		0.0458	0.0638	0.0846
q=4	0.0281	0.0419	0.0591		0.0292	0.0435	0.0612
q=5	0.0177	0.0286	0.0429		0.0184	0.0297	0.0444
q=6	0.0110	0.0197	0.0313		0.0113	0.0203	0.0323
q=7	0.0069	0.0135	0.0230		0.0071	0.0139	0.0236
q=8	0.0042	0.0092	0.0169		0.0043	0.0095	0.0174
q=9	0.0026	0.0063	0.0125		0.0027	0.0065	0.0128
q=10	0.0016	0.0044	0.0092		0.0017	0.0045	0.0094