Quantifying Knowledge Spillovers using Spatial Econometric Models

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Abstract

This paper seeks to develop our understanding of the somewhat diffuse nature of technological externalities in technological space by associating a geographical dimension with the sectoral dimension. Using a panel data set containing French patents granted as well as private and public research expenditures by industry and region over the period from 1992 to 2000, this paper estimates a knowledge production function. The region- and industry-specific nature of the sample data allows us to model spatial spillovers associated with public and private research expenditures in own- and other-industry sectors for our sample of 94 French regions. This allows us to empirically examine Jacobs externalities thought to arise from cross-industry fertilization that occurs in the innovation process, versus Marshall-Arrow-Romer (MAR) externalities arising from within-industry diffusion of innovation.

Since industry-specific patents are zero in some regions and time periods, we rely on a Bayesian spatial Tobit regression model that accommodates these zero observations. Zero patents are treated as reflecting negative utility associated with a patent, consistent with the idea that applying for a patent is a strategic decision. The Markov Chain Monte Carlo (MCMC) estimation procedure treats zero observations as latent variables indicative of negative utility values that are estimated during MCMC sampling. This allows calculation of the remaining model parameters based on distributions that condition on the estimated latent variable values. We find that the largest direct and indirect effects are associated with private R&D activity that spills across industry boundaries. However, since Jacobs externalities decrease more drastically with distance than MAR externalities, our results also point to different optimal strategies for regional versus national officials.

KEYWORDS: MAR externalities, Jacobs externalities, spatial spillover effects, Bayesian Markov Chain Monte Carlo.

JEL CODES: O31, R12,C11

1 Introduction

The question of the intra- or intersectoral origin of knowledge externalities is crucial for understanding innovation mechanisms and the dynamics of growth and localization that derive from them (Duranton and Puga, 2001, Duranton, 2006). The relevant theoretical viewpoints however, are subject to widespread debate in growth analyses where Marshall-Arrow-Romer (MAR) and Jacobs externalities are in opposition. The specialization viewpoint (MAR) is that spillovers are more likely to occur between similar firms, sharing common knowledge. An implication of this is that regions where firms are specialized in a particular industry should benefit from increasing returns and produce more innovation output. Conversely, the diversification view (Jacobs) is that knowledge spillovers are enhanced by cross-fertilization and complementarities between firms. Taking this view, regions with diversified production should produce more innovations because complementary knowledge is what gives rise to increasing returns.

These issues are relevant for thinking about spatial clustering and formation of industrial parks. Indeed, cluster-based technological policies are expanding rapidly. The European Union is reinforcing its clusters policy (Communication of the European Commission, October 17th, 2008) to foster innovation and improve economic performance. Spatial clustering policies rely on a theoretical argument that specialization increases pecuniary and knowledge externalities between agents. However, the theoretical as well as empirical literature stress that diversity may be an important source of externalities as well. Therefore, the motivation of this paper is twofold. Firstly, it aims at quantifying the magnitude of intra and interindustry spillovers as well as their spatial extent. Secondly, it provides a formal econometric motivation for the existence of spatial dependence and applies an appropriate spatial econometric model.

There are two streams of empirical literature that address these issues. The first one focuses primarily on the role played by industrial structure. Distinguishing between the sectoral origin of technological externalities they mostly conclude that both kinds of externality exert a significant impact on productivity growth or innovation. While some focus on the intrasectoral dimension (Jaffe 1986, Rosenthal and Strange 2001, Henderson 2003), others stress cross-fertilization mechanisms (Glaeser and al. 1992, Fung and Chow

2002), or even the negative effects of specialization (Audretsch and Feldman 1999, Greunz, 2004). Some recent studies consider both the spatial and sectoral dimension of technological spillovers. Oerlemans and Meeus (2005) and Capello and Faggian (2005) analyze the impact of proximity and industrial organization on innovation and firm performance. They conclude that both intra and interindustry spillovers may arise. However, they do not test the spatial extent of these phenomena. Cantwell and Piscitello (2005) are among the rare studies that observe to what extent intra and interindustry spillovers decrease with distance. Their measure of both specialization and diversity exert a decreasing effect on the number of patents granted to multinational enterprises. However, they do not fully account for potential spatial dependence, since only lagged independent variables are included.

The second stream of literature examines spatial or geographical aspects of spillovers. Only few of these studies have attempted to assess the question of sectoral or industry origins. Autant-Bernard 2001 and Bottazi and Peri 2003 incorporate a measure of technological similarity between regions in conjunction with spatial proximity measures. More recently, LeSage, Fisher and Scherngell (2007) introduce a technological proximity indicator in the knowledge production function and find that it leads to a reduction in the role played by spillovers linked to geographical distance. Parent and LeSage (2008) show that a model that relies on a mixture of technological and spatial connectivity of regions is superior to models based on either type of connectivity alone. Because these studies did not use sample data that included industry-specific information, they cannot provide a great deal of insight into the nature of interindustry versus interregional influences on innovation.

Therefore, this paper seeks to develop our understanding of the somewhat diffuse nature of technological externalities in technological space by associating a geographical dimension with the sectoral dimension. In particular, this involves testing whether intersectoral externalities would be more favored by geographical proximity, while intrasectoral externalities would be produced more easily at a distance. Such an assumption relies on several theoretical arguments. First intrasectoral knowledge (i.e., knowledge specific to a sector) — which is more readily assimilated — would be transmittable at a distance. Conversely, since each sector has its own language, geographical proximity would be required to compensate for technological distance between sectors. Second, the geographical proximity may enhance the opportunities for face-to-face contacts. This can allow knowledge flows between people working in very different sectors. They interact because they are located close by, whereas at a distance they would have no opportunity to meet each other. Conversely, people working in the same sector may have opportunities to interact even if they are located at a distance through commercial relations, formal meetings, and so on. Finally, proximity may be such that the positive effects of knowledge externalities are cancelled out by competition effects which encourage spatial differentiation of innovation activities.

Following the geography of innovation literature, the model is based on a knowledge production function, taking into account both geographic and sectoral spillovers. An evaluation of the geographical dimension of knowledge externalities can then be provided, together with an assessment of their sectoral dimension. From a methodological perspective, this paper provides a number of contributions. First our study properly treats spatial dependence in the dependent variable that reflects knowledge output. The source of this type of dependence is motivated using a formal econometric argument. Beginning with a non-spatial knowledge production function we show how the presence of unmeasurable/unobserved regional inputs to the knowledge production process lead to a spatial regression model that includes a spatial lag of the dependent variable as well as the independent variables. This type of model has been labeled a spatial Durbin model (SDM) in the spatial econometrics literature. Our approach to arriving at a spatial regression model specification differs that of Fingleton and López-Baso (2006), Ertur and Koch (2008), who directly include spatial dependence structures in theoretical economic relationships to arrive at spatial regression models.

A second methodological contribution of our study is correct calculation of the response of industry-level regional patents to changes in own- and other-industry R&D inputs to the knowledge production process. Specifically, we measure own-partial derivatives $\partial y_{iu}/\partial x_{iv}$, as well as cross-partial derivatives $\partial y_{iu}/\partial x_{jv}$, where y_{iu} denotes region i industry u patent outputs and x_{jv} reflect region j, industry v R&D inputs. In our spatial model, these differ from the partial derivatives of conventional non-spatial regression relationships. For non-spatial regressions, the coefficient estimates lead directly to measures of the response of y_{iu} to variation in the levels of various knowledge production inputs, x_{iu}, and there are no spatial spillover impacts, so changes in inputs of other regions j do not influence region i, e.g., $\partial y_{iu}/\partial x_{jv} = 0$. In the case of the SDM model, $\partial y_{iu}/\partial x_{jv}$ takes a much more complicated form and allows for spatial spillover impacts from changing inputs x_{jv} in one region j on y_i in other sample regions $i \neq j$. Specifically, the partial derivative takes the form of an n by n matrix, where the diagonal elements of the matrix reflect "direct effects" or own-region partial derivatives, and the off-diagonal elements represent "indirect effects" (spatial spillovers) or cross-region partial derivatives.

We report scalar summary measures for the n by n matrix of direct and indirect effects on industry-level regional patents that arise from changes in own- and other-industry private and public R&D expenditures. This is done using methods from LeSage and Pace (2009) that allow us to quantify the relative importance and statistical significance of Jacobs versus MAR externalities, something not done in previous studies.

Section 2 sets forth the theoretical model and assumptions that lead to a spatial Durbin regression model. This section also includes a discussion of interpretation of the model in terms of "direct", "indirect" and "total" effects estimates. These "effects" estimates reflect the responsiveness of patents to regional own- and other-industry private and public R&D expenditures, our object of interest.

Section 3 applies the model to a space-time-industry panel of 94 French regions covering the period from 1992-2000.

2 The knowledge production model

Section 2.1 sets forth a spatial econometric theoretical motivation for our empirical spatial Durbin model (SDM) based on the observation that in addition to measurable inputs to regional knowledge production, there are also unmeasurable inputs. In Section 2.2 we turn attention to the fact that our dependent variable reflects patents which take on values of zero for some industries, time periods and regions. This problem is overcome by treating zero patents as reflecting negative utility associated with patents in a particular industry, time or region, leading to a spatial Tobit model. Section 2.3 turns attention to interpreting the spatial effects of changes in inputs to the knowledge production process (the explanatory variables of the SDM model) on patenting activity (the dependent variable).

2.1 A theoretical motivation

The objective is to estimate the potential extent, scale and geographical dimension of knowledge externalities. The Griliches-Jaffe knowledge production function (KPF) provides a useful modelling framework for this. In very broad terms, this takes the following form:[1]

$$I = \alpha_1 r + r^\star \tag{1}$$

Where the vector I represents a (logged) vector of TMN observations on N regions innovation output across T time periods and M industry categories. The explanatory variable vector r represents regional (logged) inputs to the innovation production process across regions, time and industries, with r reflecting observable/measurable private and public R&D inputs. It seems reasonable to assume that there are unobservable/unmeasured inputs to the innovation production process arising from both private and public research activities. Since measuring inputs to innovation seems notoriously difficult, we let $r^\star$ denote unmeasured inputs that are excluded from the explanatory variable set in (1).

It has become a stylized fact that empirical measures of variables associated with regional knowledge production such as r in (1) exhibit spatial dependence (see Autant-Bernard (2001, Autant-Bernard et al. 2007), Parent and LeSage (2008)). If both the measurable variable r included in the empirical relationship (1) and the unmeasurable excluded variable $r^\star$ exhibit spatial dependence, then we can show that a spatial regression relationship will result.

Specifically, let the spatial autoregressive processes in (2) and (3) govern spatial formation of observable and unobservable inputs to the knowledge production process: r and $r^\star$. Although we let r denote a single vector variable representing observable regional knowledge production inputs, without loss of generality our results can be established for the case of a matrix R of observable production inputs. We have introduced zero mean, constant variance disturbance terms u, v, ε, along with an N by N spatial weight matrix W reflecting

[1] For simplicity of presentation we ignore time-specific intercept terms and fixed effects parameters for industries in this presentation, all of which are included in our empirical implementation of the model. We also assume I, r and $r^\star$ are in log form and for simplicity work with vector inputs r and $r^\star$.

the connectivity structure of the regions. The matrix $\tilde{W}$ in (2) and (3) equals $I_T \otimes I_M \otimes W$, by virtue of our assumption regarding the stacking order of the vectors $I, r, r^\star$.[2] The scalar parameters ϕ and ψ reflect the strength of spatial dependence in r and $r^\star$.

$$
\begin{aligned}
r &= \phi \tilde{W} r + u && (2)\\
r^\star &= \psi \tilde{W} r^\star + v && (3)\\
v &= u\gamma + \varepsilon && (4)\\
u &\sim N(0, \sigma_u^2 I_n) && (5)\\
v &\sim N(0, \sigma_v^2 I_n) && (6)\\
\varepsilon &\sim N(0, \sigma_\varepsilon^2 I_n) && (7)
\end{aligned}
$$

The relationship in (4) reflects simple (Pearson) correlation between shocks (u, v) to the observable and unobservable inputs to the knowledge production function r and $r^\star$ when the scalar parameter $\gamma \neq 0$. We let $n = TMN$ in (5) and (6).

If we begin with the relationship in (1) and use the definitions in (2) to (7) we arrive at (8), where y denotes the vector I.[3]

$$
\begin{aligned}
y &= \psi \tilde{W} y + r(\beta + \gamma) + \tilde{W} r(-\psi\beta - \phi\gamma) + \varepsilon \\
y &= \psi \tilde{W} y + r\beta_1 + \tilde{W} r \beta_2 + \varepsilon && (8)\\
\beta_1 &= (\beta + \gamma) \\
\beta_2 &= (-\psi\beta - \phi\gamma)
\end{aligned}
$$

The expression in (8) represents what has been labeled a spatial Durbin model (SDM) by Anselin (1988). This model subsumes the spatial error model SEM: $(I_n - \psi\tilde{W})y = (I_n - \psi\tilde{W})r\beta_1 + \varepsilon$, as a special case when the parameter $\gamma = 0$ indicating no correlation in

[2]We assume observations are stacked by time, then industry, then region. That is, all regional observations for time 1, industry 1 are first, then all regional observations for time 1, industry 2. After all M industries for time 1, we begin with industry 1 for time 2 all regions and so on.

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

shocks to measured and unmeasured regional inputs to the knowledge production process, and when the restriction $-\psi\beta_1 = \beta_2$ is true.[4] Another way to view this is that the SDM model nests the SEM model as a special case that arises when the parameter restriction is consistent with the sample data.

The condition $\gamma \neq 0$ indicates that the included variables r and excluded variables $r^\star$ are correlated. (Correlation between the shocks, u, v implies correlation between r and $r^\star$.) Conventional omitted variables treatment considers the non-trivial case where correlation exists between included and excluded variables. A related point is that $\gamma \neq 0$ will lead to a rejection of the common factor restriction, since the coefficient restriction on β_2 will not hold when $\gamma \neq 0$. We note that even if $\gamma = 0$, it would still be possible to reject the coefficient restriction and therefore the SEM model in favor of the SDM model. That is, $\gamma = 0$ is a necessary but not sufficient condition for the SEM model. We conclude from this that an omitted variable that is correlated with inputs to the knowledge production process included in the model will lead to a spatial regression model that must contain a spatial lag of the dependent variable.

This development provides a formal motivation for inclusion of what is known as a "spatial lag" of both dependent ($\tilde{W}y$) and explanatory variables ($\tilde{W}r$) in our regression relationship that seeks to explore knowledge spillover effects. Our development is unlike that in theoretical models of Fingleton and López-Baso (2006), Ertur and Koch (2007), who directly include spatial dependence structures in theoretical economic relationships to arrive at spatial regression models. Our staring point is a non-spatial theoretical relationship where included and excluded explanatory variables reflecting regional inputs to a knowledge production process are correlated by virtue of spatial dependence in both measurable and unmeasurable inputs.

2.2 A spatial Tobit model

In our exploration we use industry-specific patents granted as the dependent variable, reflecting output from regional innovation production processes over both time and space. This measure has the advantage that it reflects a direct output of R&D processes, but is

[4] Anselin (1988) labels this restriction a "common factor restriction".

also problematical since we observe zero counts of industry-specific patents granted in regions during some time periods. Specifically, in our sample of size $TMN = 9,306$, we have 1,243 cases of zero patents, or 13.35 percent of the sample. Given this small percentage of zero values, a Poisson model representing cumulated regional patenting activity as a rare event seems problematical, motivating our use of a spatial Tobit model (LeSage and Pace, 2009).

Of course, not all inventions are patented for a host of reasons. First, filing for a patent reflects a strategic decision on the part of the inventor. There are costs and benefits associated with filing, and in some cases the strategic costs may outweigh the benefits (there is for instance a well-known trade off between patenting and keeping secret the invention). Secondly, an invention must be perceived as both a new and useful process, machine, manufacture or composition of these or materials, and incorrect perceptions on the part of the inventor may lead to a decision not to patent.

Innovation is an uncertain process. Valuable outcomes do not always arise from R&D investments. In addition, the result of R&D may be patented in another region. We lump all of these issues under the broad rubric of perceived negative utility associated with patenting of certain inventions.

This allows us to rely on a Bayesian spatial Tobit regression model (LeSage, 2000, LeSage and Pace, 2009) that accommodates zero observations of the dependent variable, treating them as latent observations reflecting negative utility associated with the patenting decision. Bayesian Markov Chain Monte Carlo (MCMC) estimation methods can be used to estimate the spatial Durbin model where negative utility values are estimated for the zero observations conditional on the non-zero observations during MCMC sampling. Replacing the zero values of the dependent variables with these continuous (negative) variables allows sampling the remaining model parameters based on distributions that condition on the estimated latent variable values. Details regarding this procedure are set forth below.

Let the vector $y = I$ be partitioned into $y_1 > 0$ and $y_2 = 0$, where we will use the definition $n \equiv TMN$ in the following discussion for simplicity. The matrix $\tilde{W}$ can be similarly partitioned based on the n_1 observations for y_1 and n_2 observations for y_2, allowing us to express our SDM model as:

$$\begin{pmatrix} y_1 \\ y_2 \end{pmatrix} = \psi \begin{pmatrix} W_{11} & W_{12} \\ W_{21} & W_{22} \end{pmatrix} \begin{pmatrix} y_1 \\ y_2 \end{pmatrix} + \begin{pmatrix} X_1 \\ X_2 \end{pmatrix} \beta + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \end{pmatrix} \tag{9}$$

Where X equals $\begin{pmatrix} r & \tilde{W}r \end{pmatrix}$ and X_1, X_2 represents partitions based on the n_1, n_2 non-zero and zero observations.

To implement MCMC estimation we need to sample sequentially from the complete sequence of conditional distributions of the model parameters, ψ, σ^2, β, as well as the conditional distribution for the zero-valued observations in y_2. The zero-valued observations are sampled conditional on the non-zero values in y_1, and the other parameters of the model. In essence, the zero-valued observations are being treated as additional parameters in the model that require estimation. The conditional distribution of $(y_2|y_1)$ takes the form of a truncated multivariate normal distribution with a mean set forth in (10), and variance in (11). This result is based on the model from (9) and standard multivariate normal distribution theory.

$$E(y_2|y_1) = \mu_2 + \Sigma_{21}\Sigma_{11}^{-1}(y_1 - \mu_1) \tag{10}$$

$$\text{var}(y_2|y_1) = \Sigma_{22} - \Sigma_{21}\Sigma_{11}^{-1}\Sigma_{12} \tag{11}$$

Where:

$$\begin{aligned} Z &= I_n - \psi\tilde{W} \\ \Psi &= Z'Z \\ \Sigma &= Z^{-1}(Z')^{-1} = \Psi^{-1} \\ \mu &= Z^{-1}X\beta \\ \mu &= \begin{pmatrix} \mu_1 & \mu_2 \end{pmatrix}' \end{aligned}$$

Pace and LeSage (2007) point to some computational savings that can be obtained by noting that use of (10) and (11) requires finding the inverse of the n by n matrix Z. Since the matrix $\tilde{W}$ is sparse, containing a large number of zeros, we would like to avoid inversion since this will result in a matrix with non-zero elements.[5] They use Corollary 8.5.12 in Harville (1997):

$$\Sigma_{21}(\Sigma_{11})^{-1} = -(\Psi_{22})^{-1}\Psi_{21} \tag{12}$$

which allows us to express the conditional mean as:

$$\begin{aligned}
E(y_2|y_1) &= \mu_2 - (\Psi_{22})^{-1}\Psi_{21}(y_1 - \mu_1) \\
\Psi_{21} &= -\psi W_{21} \\
\Psi_{22} &= I_{n_2} - \psi W_{22} \\
E(y_2|y_1) &= \mu_2 + (I_{n_2} - \psi W_{22})^{-1}\psi W_{21}(y_1 - \mu_1) \\
\mu &= (I_n - \psi W)^{-1} X\beta
\end{aligned}$$

Pace and LeSage (2007) also point to computational savings that can be employed for the variance calculation based on:

$$\begin{aligned}
\mathrm{var}(y_2|y_1) &= \Sigma_{22} - \Sigma_{21}\Sigma_{11}^{-1}\Sigma_{12} \\
\mathrm{var}(y_j|y_{\forall i \neq j}) &= 1/d_j \\
d &= \iota_n + \psi^2(\tilde{W}' \odot \tilde{W}')\iota_n
\end{aligned} \tag{13}$$

Where the Hadamard product term $(\tilde{W}' \odot \tilde{W}')\iota_n$ only needs to be computed once. This simplification arises because the diagonal elements of $Z'Z$ are just the sum of squared elements in each column of Z. Since the diagonal elements of Z always equal 1, the contribution of the squared diagonal to the sum of squared elements in each column equals 1. The off-diagonal elements equal ψ times the corresponding column of $\tilde{W}$ (see LeSage and Pace

[5] Inversion of sparse matrices results in "fill-in" of zero values with non-zero values, which greatly increase memory requirements and time required for matrix multiplication.

(2009) for a more detailed exposition).

Sampling for the remaining parameters of the model, ψ, β, σ can be accomplished using the conditional distributions for these parameters described in LeSage (1997), where the vector $\tilde{y}$ containing the sampled values for y_2 are used to replace the zero-valued observations in the dependent variable vector y.

2.3 Interpreting the spatial model estimates

An empirical implication of our spatial Durbin regression model is that calculation of the response of innovation measured by industry u patents in region i, y_{iu} to the vth knowledge production input in region j from the matrix of inputs X, e.g., $\partial y_{iu}/\partial x_{jv}$ will differ from conventional non-spatial regression models. In the case of the SDM model, $\partial y_{iu}/\partial x_{jv}$ takes a much more complicated form and allows for spatial spillover impacts from changing variable x_{jv} in one region j on y_i in other regions $i \neq j$ in the sample. We consider these impacts for the model in (14), using the n by n matrix defined in (15), which contains an index u to denote association of this matrix with parameters α_{1u} and α_{2u} for the uth explanatory variable in the matrix X.

$$y = \psi \tilde{W} y + \alpha_0 + X\alpha_1 + \tilde{W} X \alpha_2 + \varepsilon \tag{14}$$

$$S_u = (I_n - \psi \tilde{W})^{-1}(I_n \alpha_{1u} + \tilde{W}\alpha_{2u}) \tag{15}$$

The direct impact from changing the uth variable in region i, (x_{iu}) on y_{iu} in region i would be $\partial y_{iu}/\partial x_{iu}$ which is represented by the i,ith element from the diagonal of the matrix S_u. The cross-partial, or $\partial y_{iu}/\partial x_{ju}$ is the i,jth element from the matrix S_u.

We note that changing observation i only influences other observations in the spatial cross-section, but not in other time periods, since the matrix S_u is block-diagonal matrix, given that $\tilde{W}$ is block diagonal, containing a separate N by N block for each time period and each industry, where N denotes the number of regions in our sample. Our model partitions the explanatory variables X into own- and other-industry inputs, which we denote as u and v, respectively. This allows interindustry effects to be assessed by considering changes in other-industry inputs, x_{iv} on knowledge production output of industry u in regions i or j, captured by $\partial y_{iu}/\partial x_{iv}$ or $\partial y_{ju}/\partial x_{iv}$. When analyzing own- and cross-partial impacts, we average these over all time periods and industries by pooling our sample data. That is, we produce a single inference regarding the direct and indirect (spatial spillover) impacts that arise from changes in own- and other industry inputs (both private and public R&D inputs) on own- and other-region patenting output behavior. We will have more to say about the logic of this when we describe the empirical implementation of our model.

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 proxy knowledge available in other regions by either a spatial lag of innovation output from neighboring regions measured through their patents (Anselin Varga, and Acs, 1997), or by explanatory variables reflecting research effort in neighboring regions. They then proceed to assess the magnitude and significance of impact from spatial spillovers using the parameters associated with these spatially lagged explanatory variables. It should be clear that the coefficient α_2 used in past studies is an incorrect representation of the impact of changes in the uth variable on y. In fact, the parameter α_{2u} 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 impacts arising from changes in the uth explanatory variable on the dependent variable vector representing regional innovation y. They point out that the main diagonal elements of the matrix: $S_u = (I_n - \psi\tilde{W})^{-1}(I_n\alpha_{1u} + \tilde{W}\alpha_{2u})$ represent own partial derivatives, which they label direct effects and summarize using an average of these elements. 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.

A final point is that simultaneous feedback is a feature of the equilibrium steady-state for the spatial Durbin model that allows for spatial dependence relations. Feedback effects can arise from changes in the explanatory variables of region i that will potentially exert impacts on all other regions. In the context of our static cross-sectional model where we treat observations as reflecting a steady state equilibrium outcome, these feedback effects appear as instantaneous, but they can be interpreted as representing a sequence that would occur over time during movement to the next steady state.

3 Empirical implementation

The empirical model and data are described in Section 3.1, with estimation results reported in Section 3.2. Estimates of the direct, indirect and total effect on innovation output arising from changes in private and public own- and other-industry inputs to the production process are analyzed in Section 3.3. Section 3.4 provides a spatial profile of the spillovers as they relate to order of neighboring regions.

3.1 The empirical model and data

We implement the model using a panel of 11 industries covering the nine years from 1992 to 2000 and 94 French regions. The regions are metropolitan French "départements", which are administrative units. They roughly correspond to a city and its suburbs. Spatial connectivity is based on contiguity, which has a certain intuitive appeal here, since historically French "departments" were defined in relation to the distance surrounding a central town, based on one day's travel by horse. Results obtained based on a distance-based spatial weight matrix W should therefore be similar to those obtained using the contiguity-based matrix W.

We pooled over all time periods, industries and regions to provide a single set of estimates that measure the direct, indirect and total effects arising from changes in own- and other-industry private and public R&D inputs to the knowledge production process on innovation output measured by patents in each industry, time period and region. To control for the pooling aspect of our model implementation, we introduce time- and industry-specific fixed effects, leading to the model in (16).

$$
\begin{aligned}
y &= \psi\tilde{W}y + \sum_{j=1}^{11}\alpha_j \mathrm{IND}_j + \sum_{j=1}^{9}\beta_j \mathrm{YR}_j + \mathrm{RD}_i\gamma_1 + \mathrm{RD}_k\gamma_2 + \mathrm{PUB}_i\theta_1 + \mathrm{PUB}_k\theta_2 \\
&+ \tilde{W}\mathrm{RD}_i\gamma_3 + \tilde{W}\mathrm{RD}_k\gamma_4 + \tilde{W}\mathrm{PUB}_i\theta_3 + \tilde{W}\mathrm{PUB}_k\theta_4 + \mathrm{ES}_i\rho + \varepsilon \qquad (16)
\end{aligned}
$$

Where y denotes innovation output (the dependent variable) measured as the number of patents filed in each of the 94 regions (source: OST - the French Observatory for Science & Technology), time periods and industries. The regions correspond to the French department in which the inventor is located, providing an accurate reflection of the geographical area where the innovation was produced. The dependent as well as independent variables are smoothed over 3 years to reduce noise arising from annual variation, since our analysis seeks to focus on long-run equilibrium phenomena.

The explanatory variables RD and PUB reflect private and public inputs to the innovation production process, with RD_i denoting own-industry private R&D inputs and RD_k representing other-industry private R&D inputs. Similarly, PUB_i represents own-industry public R&D inputs while PUB_k is other-industry. We wish to measure average direct and indirect effects arising from private versus public research inputs on the number of patents, separated into own- and other-industry categories (pooled over all regions and time periods). Indirect (spatial spillover) effects arising from own-industry inputs will be compared to other-industry spatial spillovers for both private and public inputs. Own-industry effects on innovation reflect MAR externalities whereas other-industry spillover effects capture Jacobs externalities. The Grilliches (1979) and Jaffe (1989) knowledge production function is not typically used to analyze the sectoral dimension of knowledge externalities, but this offers a more realistic reflection of research and innovation and facilitates a better understanding of the role of diversity and specialization. In previous studies investigating the impact of agglomeration economies on innovation, the regional output of innovation is explained by specialization or diversity indices, such as the index of revealed technological advantage (Feldman and Audretch, 1999, Paci and Usai, 2000, Massard and Riou, 2003). This is also the method followed in productivity growth regressions. But, this leads to a rather indirect assessment of externalities. The impact of local available stock of knowledge (private and public) is somewhat neglected. This is why we use direct measures of the industrial structures here, captured by measures of the level of intra and interindustry activity.

The structure assigned to govern dependence relationships in the dependent variable, y (industry-level regional patents over time) does not allow for simultaneous interindustry dependence in y as it does for spatial dependence between regions. The simultaneous spatial dependence is captured by the spatial lag of the dependent variable. A lack of simultaneous interindustry dependence should not be construed to mean that our model cannot capture inter-industry effects, but rather that these are modeled using the explanatory variables reflecting own- and other-industry (public and private) R&D activity. This allows us to produce a single inference regarding how changes in own- and other-industry R&D inputs impact own- and other-industry knowledge outputs.

There are good reasons to avoid a model that allows for simultaneous interindustry spillovers modeled using an interindustry connectivity matrix similar to the spatial connectivity matrix W. Introducing an interindustry structure of dependence between elements of the y vector in addition to spatial (and possibly time dependence) would greatly complicate interpretation of the coefficient estimates. As we have seen in Section 3.3, dependence between spatial elements of the y vector produce simultaneous feedback effects that must be taken into account when interpreting the partial derivative effect of changes in the explanatory variables on y. If we allowed for interindustry dependence in y as we did for space using a matrix similar to W, interpretative complications could arise when considering the partial derivative impact of a change in own- and other-industry R&D activity on y. The spatial configuration of our regional observations is fixed over time, whereas the interindustry structure of dependence is likely to evolve over time. If changes in the explanatory variables imply changes in the interindustry dependence structure, changes in these variables would have two impacts on the dependent variable y. One would be associated with the change in explanatory variable, and the second would arise from the implied change in the interindustry dependence structure.[6]

Our model could be criticized for not treating all possible space-time-industry covariance

[6]It seems plausible that both changes and levels of the explanatory variables over time (industry-specific public and private R&D) might lead to changes in the interindustry connectivity structure. This means that difficulties of interpretation are not a vacuous concern.

relationships in an even-handed fashion. We take the view that for a first-cut analysis, time- and industry-specific fixed effects plus conditioning on the own- and other-industry $R\&D$ explanatory variables that are time and region-specific can adequately model the non-spatial interdependence relationships. Extensions to the more general cases are a subject for future research.

Mapping industry-specific innovation inputs and output required various databases to be aligned. The patents were split into 30 technical fields, private R&D inputs into 25 research sectors and public R&D measured using scientific publications in 8 scientific disciplines. To make these databases mutually coherent, we had to construct a horizontal classification covering 11 industries: Chemistry, Pharmacy, Energy, Electricity, Electronics and IT, Instrumentation, Mechanical Engineering, Materials, Aerospace, Food, Transport.[7]

We rely on relatively broad industry classifications in contrast to previous studies, where authors treat intra-sectoral externalities using very narrowly defined sectors (4-Digit for instance). Our low number of sectors may be justified for two reasons enumerated below.

First, the three classifications used here to define (30 technological fields, 25 R&D sectors and 8 scientific disciplines) are not nested, each of them relying on its own logic. This problem does not arise in studies considering agglomeration phenomena instead of knowledge externalities. Indeed, in such studies (Glaeser et al. 1992, Henderson et al. 1995, etc.), all variables (employees, firms, etc.) are from the same classification. Here, with innovation data, a narrow definition of industries would lead us to consider some externalities as inter-sectoral whereas in fact they are intra-sectoral.

Second, despite the use of rough definitions, these allow us to address most of the questions regarding specialization of cities. Indeed, innovative clusters are rarely narrowly specialized. The well-known firms of the Silicon Valley do not belong to the same four-digit industry, yet there is little argument that they benefit from specialization economies.

The variable ES_i is a control for the economic size of an industry in each region, con-

[7] To do this, we first converted our patent and R&D data from French classifications to international classifications (respectively IPC and ISIC). This was done on the basis of the OST report, allowing use of the link between IPC and ISIC made by researchers from the MERIT (Verspagen, Moergastel and Slabbers). Using the OST report that details each scientific field, we built the concordance with the public research classification. Although this work was done before the report of the European Commission "Linking technology areas to industrial sectors" (2003), most of our results are similar. Our methodology differs however, since we chose to allow one technological field to be linked to several R&D sectors.

structured using the number of employees within each region's industries, based on the "EAE" Annual Company Census (Ministry of Industry) results. This data is collated according to the French Activities Classification (NAF). Translation to the 11-sector nomenclature was completed using the official cross-reference table, aligning the NAF and the R&D survey research codes (source: Ministry of Research).

Spatial lags of both the dependent and independent variables are included in the model based on our theoretical motivation that there exist omitted variables reflecting inputs to the knowledge production process. These are assumed to be correlated with the included variables, an assumption that can be tested using the restriction that the parameters: $\gamma_3 = -\psi\gamma_1, \gamma_4 = -\psi\gamma_2, \theta_3 = -\psi\theta_1, \theta_4 = -\psi\theta_2$.

3.2 Estimation results

We wish to provide "scale-free" average measures of the responsiveness of innovation activity measured by region-industry-time specific patenting to changes in own- and other-industry private and public research inputs. Since the magnitude of other-industry research inputs vastly exceeds own-industry in most if not all cases, a log transformation to both the dependent and independent variables allows us to draw inferences regarding the relative responses that have an elasticity interpretation. As noted, a scalar summary of the direct effects averaged over all industries, time periods and regions are based on the "own" partial derivative, while indirect effects representing spatial spillovers correspond to "cross" partial derivatives of the SDM model.

The parameter estimates (excluding the time and industry fixed effects parameters) are reported in Table 1. Maximum likelihood estimates that ignore the non-normality of the patent counts induced by the zero values are reported alongside the Bayesian spatial Tobit estimates. These illustrate that ignoring the zero values leads to a downward bias in the estimates, that is, patents appear less responsive to the explanatory variables in the case of maximum likelihood. In the discussion that follows we refer only to the Bayesian MCMC spatial Tobit estimates reported in the table. For the Bayesian MCMC estimates, a $p-$level is reported, which replaces conventional $t-$statistic probabilities and are computed based on the proportion of draws > 0 or < 0 depending on the sign of the coefficient. Gelman, et al. (1995) provide the motivation for using p-values.

We need to keep in mind that these coefficients do not correspond to the direct and indirect effects in which we are interested. However, they are useful for testing the assumptions made in constructing our model.

Table 1 about here

From the table we see that spatial dependence exist in the dependent variable, since the parameter ψ is significantly different from zero. We also see that the coefficients on RD_i and RD_k as well as the spatial lags of these variables are positive. Since the spatial dependence parameter ψ is positive, the restrictions $\gamma_3 = -\psi\gamma_1$ and $\gamma_4 = -\psi\gamma_2$ are not likely to be true. We used the set of 5,000 retained MCMC draws obtained during estimation of the model to construct a formal test of these restrictions based on the posterior distribution of the non-linear parameters $-\psi\gamma_1, -\psi\gamma_2$ and the parameters γ_3, γ_4. This test rejected the restriction suggesting that the included and excluded measures of private own- and other-industry R&D inputs are correlated, as we assumed.

Since the parameter θ_4 on $W * \mathrm{PUB}_k$ is not significantly different from zero, the restriction $-\psi\theta_2$ will not hold since both ψ and θ_2 are different from zero. Similarly, for the restriction: $-\psi\theta_1 = \theta_3$, $-\psi\theta_1$ takes a value of $(-0.1936\text{x}0.0645 = -0.0124)$, which is more than 5 standard deviations away from $\theta_3 = 0.0411$, so this restriction is not consistent with the data. This suggests that the included and excluded measures of public own- and other-industry R&D inputs are correlated as we assumed.

3.3 Spatial spillover estimates

As noted, correct interpretation of the parameter estimates from the spatial Durbin model require that we consider the own partial derivatives (direct effects) and cross-partial derivatives (indirect or spatial spillover effects) of the non-linear relationship specified by this model. Table 2 reports the scalar summary measures of direct, indirect and total effects arising from a change in the explanatory variables of the model, $\mathrm{RD}_i, \mathrm{RD}_k, \mathrm{PUB}_i, \mathrm{PUB}_k$ and the economic size variable ES_i. In addition to the mean of the scalar summary impact estimates, lower 0.01 and upper 0.99 Bayesian credible intervals are reported in the table.

These were constructed from the posterior distributions reflected by the MCMC draws.

The effects estimates can be cumulated over all regions in the sample, or partitioned to reflect the marginal effects that fall on first-, second-, third-order, etc., neighbors. The marginal effects provide information regarding the magnitude of the various effects that arise from changes in the four types of R&D activity in our model on various orders of neighboring regions. The cumulative effects estimates are discussed here, with a discussion of the marginal effects estimates set forth in the next section.

One point is that these effects estimates reflect the cumulative impacts over space that would result from a change in steady state equilibrium induced by changes in the explanatory variables of the model. This is the appropriate way to interpret the effects estimates associated with a cross-sectional spatial Durbin model. A second thing to note is that our results reflect average effects that arise from pooling over the nine time periods and eleven industries.

Table 2 about here

We can compare the direct effects in Table 2 arising from own- and other-industry private and public research to draw conclusions regarding the relative magnitudes of influence on own-region industry-level patenting activity arising from public and private R&D expenditures in own- and other-industry categories. The direct effects estimates measure how industry-specific patenting activity at the regional level responds to intra-sectoral R&D activity (both private and public) versus inter-sectoral R&D activity.

From a regional official's perspective, the relative magnitudes of the direct effects arising from the four types of R&D activity provide information on which type of activity will produce the greatest response in regional patenting activity. From a scholarly perspective, the relative magnitudes of response to the four types of R&D activity allow us to draw inferences on MAR versus Jacobs externalities accruing to the region in which this activity takes place. The MAR notion is that regional patenting activity would be most responsive to intra-sectoral public and private R&D activity, whereas Jacobs externalities would posit more response to inter-sectoral R&D activity.

In contrast, the indirect effects presented in Table 2 arising from intra- and inter-industry private and public research reflect spatial spillover effects cumulated over all regions in the sample. This should be the focus of national policy makers, since a comparison of the relative magnitudes of direct and indirect effects associated with inter- versus intra-industry research provides information about the spillover benefits arising from inter- and intra-industry research funded by region i that benefits industry-level patenting activity in all other regions j. Again the question of MAR versus Jacobs externalities can be addressed using the indirect effects estimates. Here, the effects estimates shed light on whether intra- or inter-industry R&D activity produces larger spatial spillovers to neighboring regions.

From a regional official's perspective it might be undesirable to have benefits from R&D expenditures within the region spillover to neighboring regions. However, there is some positive feedback to the region that arises from these spatial spillovers that can be measured by the direct effects estimates from our model.

As an example of this, consider the difference between the coefficient estimate for PUB_k in Table 1 of 0.0610 and the direct effect estimate of 0.0687 presented in Table 2, equal to 0.0077. This difference represents a small feedback effect associated with the spatial spillovers that arise from inter-industry public R&D, PUB_k. To see this, note that the diagonal elements of $(I_n - \psi\tilde{W})^{-1} = I_n + \psi\tilde{W} + \psi^2\tilde{W}^2 + \psi^3\tilde{W}^3 \ldots$ used to calculate the direct effects contain non-zero elements since $\tilde{W}^2, \tilde{W}^3$, etc., contain non-zero elements. This is despite the fact that the diagonal of $\tilde{W}$ contains zero elements. This reflects the fact that region i will be a neighbor to its neighbor, leading to non-zero elements on the diagonal of $\tilde{W}^2$, and possibly a neighbor to its neighbor to its neighbor, captured by diagonal elements of $\tilde{W}^3$, etc. As noted, we can interpret the effects estimates as elasticities. This means that the feedback loop magnitude of 0.0077 is very small and does not appear to be statistically or economically significant. The same is true of the differences between coefficient estimates for the other variables: PUB_i, RD_i and RD_k. We conclude that from a regional official's perspective spatial spillovers would be undesirable, since the benefits arising from feedback effects are not significant.

We will first compare the direct effects estimates for the four variables, which measure own-region patenting activity responsiveness to private and public intra- and inter-industry R&D expenditures. These results should be of primary interest to regional officials.

The direct effects estimates for intra-industry private R&D (RD_i) versus inter-industry R&D (RD_k) suggest that industry-level regional patenting activity benefits most from inter-industry R&D, since the magnitude of direct effect for this variable is around seven times that of RD_i. That is, industry-level regional patenting activity benefits more from diverse private R&D expenditures than from industry-specific expenditures. From a regional official's perspective, it would be beneficial to recruit diverse firms (that spend on R&D) to the region. We note that this result arises despite our broad classification into eleven industry categories. The fact that inter-industry externalities predominate in terms of private R&D expenditures suggests evidence in favor of Jacobs externalities. The effects estimates are positive and significant for both intra- and inter-industry private R&D expenditures, but the relative magnitudes indicate that regional patenting activity benefits more from inter-industry than intra-industry R&D expenditures, by a factor of seven. Another way to view this result is that inter-industry spillovers account for a large portion of industry-level patenting activity that takes place at the regional level.

The direct effects arising from intra- and inter-industry public R&D are roughly equal in magnitude. This suggests that industry-level patenting activity at the regional level benefits equally from industry-specific scholarship and from scholarship that pertains to other industries. Comparing the relative magnitudes of responsiveness to private versus public R&D in intra- and inter-industry categories, we see direct responses that are greatest for RD_k (0.1572), smallest for RD_i (0.0214) and somewhere in-between for both intra- and inter-industry scholarship (our proxy for public R&D) (0.0668, 0.0687).

We now turn attention to the indirect effects which measure the magnitude of spatial spillovers cumulated over all regions in the sample. The magnitude of effects from the four types of R&D can be compared to pass judgement on which type of expenditures provide the greatest spatial spillover benefits. From a national perspective this provides information on which type of R&D expenditures produce the greatest social benefits. From a regional perspective, the relative magnitude of direct versus indirect effects provides information on the extent to which individual regions can capture the benefits from within-region R&D expenditures in the various categories.

In terms of MAR versus Jacobs externalities, the indirect effects estimates allow us to draw inferences regarding the responsiveness of industry-level patenting activity to own- and other-industry R&D activity in neighboring regions. The notion of MAR externalities would be that own-industry R&D flows more easily to neighboring regions, whereas Jacobs externalities would be favored by larger indirect effects associated with other-industry R&D activity.

For private R&D, both own- and other-industry expenditures exhibit positive spatial spillovers, but those from other-industry R&D are five times the size of own-industry. This suggests that industry-specific R&D does not benefit neighboring regions as much as other-industry R&D activity. This is evidence in favor of Jacobs externalities.

We have a different result for public R&D. The indirect effects (spatial spillovers) from PUB_k (scholarship in other-industry categories) are not significantly different from zero at the 99% level, since the lower and upper 99% bounds for these impacts span zero. This suggests that only industry-specific scholarship leads to an increase in industry-level patenting activity in neighboring regions. This seems consistent with the field-specific nature of scientific research, where disciplinary-specific barriers exist that prevent diffusion to scholars working in other disciplines. Disciplines tend to have their own terminology, methodologies and scholarly outlets that are often not accessible to those outside the discipline.

A comparison of the relative magnitudes of the direct and indirect effects allows us to draw an inference on the relative importance of spatial spillovers associated with the four types of R&D activity. The largest direct and indirect effects arise from private inter-industry R&D activity, suggesting that spillovers between industries within a region and between industries in neighboring regions have the greatest impact on industry-level patenting activity at the regional level. Since the direct effects magnitude of 0.1572 is greater than the indirect effects equal to 0.1023, we would conclude that regions have the ability to capture around 3/5 of the benefits that arise from inter-industry R&D spillovers. This is not the case for intra-industry spillovers where we see direct and indirect effects estimates of roughly equal magnitude. From a regional officials perspective it would be more beneficial to foster a diverse industry environment, since this results in larger inter-industry spillovers within the region. However, this also results in spatial spillovers to neighboring regions that are five times as large as the spatial spillovers arising from industry-specific private

R&D. This suggests that regional officials interest would coincide with national officials, since fostering a diverse industry environment would produce the largest own-region and other-region benefits in terms of industry-level patenting activity.

The case for a coincidence of regional and national officials interest with regard to public R&D expenditures is less clear. Here we see that spatial spillovers from own-industry scholarship result in an equal benefit accruing to own- and other-regions as indicated by the rough equality of direct and indirect effects associated with PUB_i. This would lead to a situation where regional officials might depend on national expenditures to support industry-specific R&D since a majority of benefits do not accrue to the region. However, the direct effects arising from inter-industry scholarship accrue entirely to the region, with no spatial spillover benefits. This suggests that regional officials would want to invest in support of broad scholarship, rather than attempt to support specialization of scholarship within particular industries in the region. In contrast, national officials would have an interest in promoting specialized scholarship at the regional level, seeing no spatial spillover benefits arising from support of scholarship in the broader categories.

The total effects estimates provide an interesting way to view the overall impact of private and public R&D activity in our intra- and inter-industry categories, from both a regional and national perspective. We first note that expenditures on all types of R&D activity exert positive total effects on industry-level patenting activity at the regional level, which we might expect. The relative magnitudes are such that inter-industry private R&D expenditures provide the greatest total impact on patenting activity, having an elasticity around 0.26. Discipline-specific public R&D expenditures produce an impact around one-half this size with an elasticity of 0.13.

In terms of MAR versus Jacobs externalities we might add the intra-industry total effects estimates from private and public R&D activity and compare these to the aggregated inter-industry total effects estimates. This results in 0.1772 for intra-industry private and public R&D, versus 0.3223 for inter-industry private and public R&D. This suggests that Jacobs externalities are twice MAR when taking both own- and other-region effects into account.

Some comments are in order regarding the specific context in which our findings might be interpreted. The predominance of inter-industry spatial spillovers for our sample may not be surprising for two reasons. First, previous studies have shown that high technology activities benefit particularly from a diversified industrial structure (Henderson et al (1995), Paci and Usai (2000), and Greunz (2004)). In our examination we are focusing specifically on the high technology research structure, not the general industrial structure. It seems likely that knowledge externalities are more important for these high technology sectors and these may be expropriated more easily in this type of environment. Second, the geography of European countries and the French regions within these countries that constitute our sample differs from the U.S. geography, which has been the focus of most previous studies. The European historical context is quite different, since the U.S. geography evolved simultaneously with the development of its industry, innovative activities and industrial infrastructure. For example, (Kim and Margo, 2005) state: "The root cause of the divergence and convergence of US regional economies is likely to be related to the development of an industrial and post-industrial society". Consequently, the structuring of economic activities and innovation in the US have made better use of localization externalities. In Europe however, the geographical configuration of economic activity dates back to well before the Industrial Revolution. Thus the French sectoral concentration of economic activity appears less obvious than in the U.S., since there are very few clusters in France, even by comparison with other European countries such as Italy. In the case of France, 40% of innovative activity is concentrated around Paris, the most diversified French region. It would therefore seem that the agglomeration of French innovative activities is based primarily on complementarity and sharing of knowledge between industries rather than on reinforcement of industry-specific innovation associated with specialization.

3.4 The spatial profile of impacts

The geographical scope of MAR and Jacobs externalities as well as the perspective of regional versus national officials can be addressed using the structure of the impact estimates to provide a spatial profile of the direct, indirect and total impacts. As already noted, this is accomplished using the infinite expansion of $(I_n - \psi\tilde{W})^{-1}$. The impacts falling on immediate (first-order contiguous) neighbors is captured by: $\psi\tilde{W}(I_n\alpha_{1k} + \tilde{W}\alpha_{2k})$, impacts on second-order (neighbors to the neighbors) by $\psi^2\tilde{W}^2(I_n\alpha_{1k} + \tilde{W}\alpha_{2k})$, and so on (see LeSage and

Pace 2009). The impact estimates in Table 2 represent the sum of the infinite series used to calculate the spatial partitioning of the impacts presented here.

Results from this type of decomposition applied to the indirect impact estimates reflecting spatial spillovers are presented in Table 3 for the four explanatory variables in our model, with results for the total impacts shown in Table 4. Lower and upper 95% confidence intervals are also presented in the tables, indicating when the impacts decay to zero as we move farther in space.

Table 3 about here

From Table 3, we see that spatial spillovers associated with the PUB_k variable are not significantly different from zero even for first-order neighbors, since the lower and upper 95% bounds for these impacts span zero. This is of course consistent with the cumulative effects results reported in Table 2 for this variable.

All other variables exhibit positive and significant spatial spillover effects. The profile of decay over space is very rapid, with the impacts on second order neighbors falling to less than 1/6 that found for the first-order neighbors, for all three variables: $\mathrm{RD}_i, \mathrm{RD}_k, \mathrm{PUB}_i$. This is consistent with previous research (Anselin, Varga and Acs 1997, Autant-Bernard 2001, Bottazzi and Peri 2003). The impacts on first-order spatial neighbors for RD_k are over four times that of RD_i, and those for PUB_i are over twice that of RD_i. These results are of course consistent with our earlier discussion of the cumulative indirect effects estimates reported in Table 2, but provide additional information regarding the spatial decay of the spillovers.

The total impacts shown in Table 4 include both direct and indirect effects arising from the various types of R&D expenditures. We can assess the spatial profile of intra- and inter-industry spillovers that take into account both the own-region and neighboring spillover effects between industries and between regions.

In terms of the total effects from changes in intra- and inter-industry public R&D (PUB_k) we see that the effect on industry-level patenting activity at the regional level for first-order neighbors are positive and significant, but effects on second- and higher-order neighbors are not significantly different from zero. This suggest that inter-disciplinary scholarship does not produce spatial spillovers that travel well over space. Other research regarding the impact of university R&D has come to similar conclusions, Varga (2000).

There is an interesting difference in the spatial profile of the total effects arising from intra- versus inter-industry private R&D on neighboring regions industry-level patenting activity. The total effect of changing RD_i on first- and second-order neighbors is roughly equal, whereas the effect arising from changes in RD_k decays to around one-half by the second-order neighbors. Intuitively, it is easier to benefit from own-industry R&D in neighboring regions than from other-industry R&D, since industry specific knowledge which is more readily assimilated would be transmissible at greater distances. In addition, researchers in the same sector may have the opportunity to interact (even if they are localized) at greater distances (via commercial relations, formal meetings, etc).

In contrast, inter-industry spillovers might require geographical proximity to compensate for the fact that industry sectors have their own language and production methods which might only be overcome through opportunities for face to face contact. This could enable knowledge flows between workers in very different industry sectors, who interact because they are located close by. If these same workers were separated by distance, they would have less opportunity to meet each other.

Table 4 about here

We have not discussed the variable ES_i included in our model to control for the size of an industry within the region. The effects estimates for this variable indicate that industry size exerts a positive direct effect on industry-level patenting activity at the regional level, with a magnitude roughly equal to the effect arising from changes in both types of public R&D activity, PUB_i and PUB_k. Spatial spillover effects (indirect effects) are not significantly different from zero for the industry size variable, while the total effects are slightly smaller than changes in RD_i, which represent the smallest total effect estimate. These results imply a positive size advantage for regions having large industries on industry-level patenting activity for the region, with no spatial spillover effects.

4 Conclusion

Beginning with a non-spatial relationship between industry-level patenting activity at the regional level, we provide a theoretical econometric motivation for a spatial regression model specification. The justification for use of a spatial regression arises from unobserved R&D inputs to the knowledge production process, which seems a realistic assumption. In addition, we assume that both observable and unobservable R&D inputs exhibit spatial dependence, and these two types of inputs are correlated.

We rely on a Bayesian spatial Tobit regression model (LeSage and Pace, 2009), to deal with the fact that our space-time panel of regional industry-level patenting activity contains zero observations. These are treated as representing situations where negative utility would arise from the decision to patent an innovation. A final methodological contribution is correct interpretation of the direct and indirect effects that arise from changes in own- and other-industry R&D activity on industry-level regional patenting activity. Drawing on work by LeSage and Pace (2009), we argue that past studies using spatial regression models have not correctly interpreted the estimates from these models to accurately measure spatial spillovers. Our effects estimates are consistent with the own- and cross-partial derivatives reflecting how industry-level patenting activity in each region changes in response to changes in the four types of R&D expenditures in our model.

Our results shed light on the nature of intra- and inter-industry R&D spillovers both within regions and between regions. We find that all types of research activities, private, public and own- as well as other-industry activity have a positive effect on industry-level patenting activity at the regional level. A comparison of the relative size of effects arising from the four types of R&D activity in terms of their impact on own- versus neighboring regions raises some interesting questions from a policy viewpoint.

The own-region effects arising from cross-industry private research spillovers are largest in regions that foster a diverse (high technology) industry structure. The spatial spillover effects from this type of region are also larger than spatial spillover effects from other types of R&D activity, specifically, effects arising from public intra- and inter-disciplinary scholarship, or private industry-specific R&D activity. From a regional official's perspective promoting a diverse industry environment allows the region to capture around 3/5 of the patenting activity benefit that arises from cross-industry fertilization associated with private R&D activity. A diverse region also provides the greatest national benefit measured by the spatial spillovers which account for the remaining 2/5 of the benefits. The total elasticity of response for industry-level patenting activity from inter-industry private R&D activity is around 0.25, with the own-region response being 0.15 and other-region spillovers equaling 0.10.

For industrial R&D, national officials have an incentive to promote private R&D activity across a diverse set of industries to produce the largest overall impact on both own- and other-region patenting activity. This would also result in the largest benefits that can be captured by individual regions, so we find that National and Regional policy makers interest coincide here. Note also that Regional officials should not be interested in preventing these spillovers since they indirectly benefit from these.

The situation for public R&D activity favors discipline-specific scholarship over inter-disciplinary, with a total elasticity response of 0.13 for discipline-specific versus 0.06 for inter-disciplinary. However, the own-region versus other-region effects for discipline-specific scholarship are roughly equal, suggesting it is more difficult for individual regions to capture the benefits from this type of expenditure. Nonetheless, benefits from both types of scholarships accruing to the region are equal, and there are no spatial spillovers associated with inter-disciplinary scholarship.

For our sample data, the results point to different optimal strategies for regional versus national officials. For public R&D spillovers, regional policy makers, more interested in direct effects, might support inter-disciplinary scholarship. On the other hand, since no spatial spillover benefits arise from this type of scholarship, there is little incentive for national officials to provide support for inter-disciplinary scholarship.

The fact that we find the largest direct and indirect effects to be associated with private R&D activity that spills across industry boundaries lends support to the case for Jacobs versus MAR externalities in the case of private R&D activity. These inter-industry spillovers occur both within regions and between regions.

In terms of public R&D activity the evidence is more mixed. The benefits accruing to own- and other-region from discipline-specific scholarship are roughly equal, suggesting

MAR externalities are at work. Benefits from inter-disciplinary scholarship accrue only within the region where this activity takes place, but the benefits measured in terms of patenting activity are of equal magnitude to that from discipline-specific scholarship that can be captured by a region.

To some extent our results run counter to other findings, and perhaps to cluster policies for support of R&D. Our results indicate that investments in general research infrastructures that take a broad focus on formation of research and commercialization services, etc. may be more effective than investments targeting a particular industry or type of technology, which are typically supported by grants or specialized equipment. General research infrastructure investments would be compatible with our finding that cross-industry spillovers from private R&D activity produce the greatest increase in both own- and other-region patenting activity.

The emphasis on specialization that underlies the cluster policies may well prove less efficient in the long term. Our results suggest that regions that become locked-in to industry-specific R&D activity will generate fewer knowledge externalities both within the region itself and for neighboring regions. The magnitude of difference between the total effects arising from industry-specific R&D activity versus inter-industry activity are around five-fold. In this context, we also find that inter-industry activity exhibits direct effects on the region that are seven times larger than intra-industry, and spatial spillover benefits that are five times larger.

Finally, our results indicate that the agglomeration mechanisms associated with innovation activities arise mostly in the presence of a diversified industrial research structure. They do not however, allow us to explore other channels for the transmission of knowledge, and in particular the modalities which are more likely to favor intra-industry exchanges. In this sense, it would be worthwhile researching specific mechanisms that give rise to the diffusion of knowledge within groups of firms, perhaps using cooperative agreements between a network of firms.

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Table 1: Estimates for the Spatial Model

	Maximum Likelihood Estimates			Spatial Tobit estimates		
	Estimate	$t-$statistics	$t-$prob	Estimate	std. dev.	$p-$level
RD_i	0.0120	6.51	0.0000	0.0205	0.0027	0.0000
RD_k	0.1100	22.71	0.0000	0.1535	0.0069	0.0000
PUB_i	0.0731	14.26	0.0000	0.0645	0.0070	0.0000
PUB_k	0.0610	9.94	0.0000	0.0688	0.0083	0.0000
ES_i	0.0472	9.55	0.0000	0.0738	0.0073	0.0000
$W * \mathrm{RD}_i$	0.0053	1.45	0.1465	0.0165	0.0050	0.0005
$W * \mathrm{RD}_k$	0.0474	4.91	0.0000	0.0555	0.0129	0.0000
$W * \mathrm{PUB}_i$	0.0127	1.13	0.2554	0.0411	0.0154	0.0030
$W * \mathrm{PUB}_k$	-0.0162	-1.24	0.2123	-0.0182	0.0179	0.1550
$W * \mathrm{ES}_i$	-0.0244	-2.89	0.0037	-0.0381	0.0118	0.0005
ψ	0.3329	82.01	0.0000	0.1936	0.0168	0.0000

Table 2: Direct, Indirect and Total Effects Estimates

Variables	Lower 01	Mean	Upper 99	std
direct effect RD_i	0.0150	0.0214	0.0277	0.0027
direct effect RD_k	0.1407	0.1572	0.1726	0.0069
direct effect PUB_i	0.0507	0.0668	0.0833	0.0072
direct effect PUB_k	0.0487	0.0687	0.0882	0.0084
direct effect ES_i	0.0568	0.0729	0.0886	0.0072
indirect effect RD_i	0.0112	0.0247	0.0387	0.0061
indirect effect RD_k	0.0650	0.1023	0.1396	0.0161
indirect effect PUB_i	0.0232	0.0643	0.1096	0.0187
indirect effect PUB_k	-0.0565	-0.0059	0.0414	0.0215
indirect effect ES_i	-0.0617	-0.0286	0.0025	0.0137
total effect RD_i	0.0308	0.0461	0.0617	0.0066
total effect RD_k	0.2198	0.2595	0.3007	0.0171
total effect PUB_i	0.0821	0.1311	0.1815	0.0211
total effect PUB_k	0.0063	0.0628	0.1169	0.0236
total effect ES_i	0.0103	0.0442	0.0767	0.0141

Table 3: Spatial Profile of Indirect Impact Estimates

Order of W^r	RDi Lower 05	RDi Mean	RDi Upper 95	RDk Lower 05	RDk Mean	RDk Upper 95
$r = 1$	0.0104	0.0203	0.0303	0.0600	0.0855	0.1111
$r = 2$	0.0015	0.0031	0.0048	0.0082	0.0133	0.0183
$r = 3$	0.0003	0.0007	0.0012	0.0015	0.0030	0.0046
$r = 4$	0.0000	0.0001	0.0002	0.0002	0.0006	0.0010
$r = 5$	0.0000	0.0000	0.0001	0.0000	0.0001	0.0002
$r = 6$	-0.0000	0.0000	0.0000	-0.0000	0.0000	0.0000
Order of W^r	PUBi Lower 05	PUBi Mean	PUBi Upper 95	PUBk Lower 05	PUBk Mean	PUBk Upper 95
$r = 1$	0.0245	0.0547	0.0849	-0.0413	-0.0059	0.0295
$r = 2$	0.0034	0.0085	0.0135	-0.0064	-0.0009	0.0046
$r = 3$	0.0006	0.0019	0.0033	-0.0015	-0.0002	0.0011
$r = 4$	0.0001	0.0004	0.0007	-0.0003	-0.0000	0.0002
$r = 5$	0.0000	0.0001	0.0001	-0.0001	-0.0000	0.0000
$r = 6$	-0.0000	0.0000	0.0000	-0.0000	-0.0000	0.0000

Table 4: Spatial Profile of Total Impact Estimates

Order of W^r	RDi Lower 05	RDi Mean	RDi Upper 95	RDk Lower 05	RDk Mean	RDk Upper 95
$r = 1$	0.0104	0.0203	0.0303	0.0600	0.0855	0.1111
$r = 2$	0.0019	0.0039	0.0060	0.0103	0.0166	0.0229
$r = 3$	0.0003	0.0008	0.0012	0.0016	0.0032	0.0049
$r = 4$	0.0000	0.0002	0.0003	0.0002	0.0006	0.0011
$r = 5$	0.0000	0.0000	0.0001	0.0000	0.0001	0.0002
$r = 6$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001
Order of W^r	PUBi Lower 05	PUBi Mean	PUBi Upper 95	PUBk Lower 05	PUBk Mean	PUBk Upper 95
$r = 1$	0.0245	0.0547	0.0849	-0.0413	-0.0059	0.0295
$r = 2$	0.0043	0.0106	0.0169	-0.0080	-0.0011	0.0057
$r = 3$	0.0006	0.0021	0.0035	-0.0016	-0.0002	0.0011
$r = 4$	0.0001	0.0004	0.0007	-0.0003	0.0000	0.0002
$r = 5$	0.0000	0.0001	0.0002	-0.0001	0.0000	0.0000
$r = 6$	0.0000	0.0001	0.0002	0.0000	0.0000	0.0000