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Spatial Aspects of Innovation Activity in the US[☆]

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Abstract

This paper studies the effects of spatial concentration of innovation activity on local production of patents in the US. In doing so, we augment the standard knowledge production function with a structure that allows for spatial effects, accounting along with bilateral also for multilateral influences across states. Our findings corroborate with past evidence on the important role of state's own R&D stock and human capital in producing new inventions. In addition, external knowledge, via spatial interactions, is also a purveyor of local innovation production. The effect is stronger when we consider spatial influences from all states, in particular from the most innovative ones, and to a lesser extent from close neighboring states. Finally, spillovers are more likely to occur between states with similar technological specialization, which share common technological knowledge and pour similar technological effort.

Keywords: patents, innovation, knowledge production, spatial

JEL: C21, O31, R12

1. Introduction

Growth is primarily driven by innovation activity and technological progress (Romer, 1986). Local economic growth crucially depends not only on the innovation activity carried out locally, but also on the ability of a region to absorb external technological achievements.[1]

Although the importance of geographic proximity has been strongly emphasized in the knowledge spillover literature, as technological knowledge is highly contextual and requires frequent contacts and interactions to spill over, most of the knowledge production studies do not explicitly account for geographic

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[1]See the studies of Coe and Helpman (1995), Blomstrom and Kokko (1998), Keller (2002), Griffith et al. (2004), and Cameron et al. (2005), among others, for the impact of technological knowledge spillovers on productivity growth.

proximity. Recently, a number of studies have allowed for bilateral aspects of space in estimating knowledge production functions. For example, the studies of Peri (2005) and Bottazzi and Peri (2007) assess the effect of own R&D stock along with that of other regions', weighted by the bilateral geographic distance between them, on regional patent production, documenting evidence on the importance of external available knowledge.

However, the size of technological knowledge interaction between two countries (regions) also depends on the size of knowledge performed elsewhere. Policies towards innovation resources and market competition shape the distribution of (limited) innovation resources across space and, therefore, cross-region interactions. Nevertheless, the spatial aspect of knowledge diffusion has not received much attention in the framework of knowledge production function.

This paper studies how the spatial concentration of innovation activity shapes the production of innovation in the US. In doing so, we augment the standard knowledge production function with a structure that allows for spatial effects. We account not only for bilateral influences, but also for effects from the rest of the states in producing innovation. In this way, we avoid overestimating the effect of homegrown and external available technological knowledge in producing local innovation.

From methodological perspective, our paper extents the coventional (non-spatial) knowledge production function in the following ways. First, we treat properly spatial dependance in the dependent variable that reflects knowledge output. Beginning with a non-spatial knowledge production function we show how the presence of unobserved regional inputs of the knowledge production process leads to a spatial regression model that includes a spatial lag of the dependent variable as well as the independent variables.

Second, we are able to properly measure the marginal effects of the response of regional innovation production to changes in own- and other-region knowledge inputs (R&D and Scientists), as in our spatial model, these effects differ from the partial derivatives of conventional non-spatial regression relationships. We can calculate own-partial derivatives $\vartheta y_i / \vartheta x_{ki}$, as well as cross-partial derivatives $\vartheta y_i / \vartheta x_{kj}$, where y_i denotes region i patent output and x_{kj} reflects region's j, k-input. In non-spatial set-ups, changes in inputs of other regions j do not affect region's i production of innovation, implying $\vartheta y_i / \vartheta x_{kj} = 0$. Specifically, the partial derivative takes the form of an nxn 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.

Our empirical analysis examines 50 states of the US and for the period 1993-2006 with two sets of questions in mind: (i) Does local patent production benefit from geographic proximity? In particular, is the effect from the average state on local patent production any different from that of the close neighbors and of top innovator states? (ii) Does local patent production benefit from technological proximity? In particular, do technologically similar states exchange more (less) spillovers than technologically dissimilar ones?

The question of knowledge externalities is crucial for understanding innovation mechanisms and the dynamics of growth and localization. Our paper adds to the spillover literature by quantifying innovation spillovers and contributing to the specialization versus diversification debate and occurrence of spillovers. The specialization approach, proposed by Marshall (1890), Arrow (1962), and Romer (1986) (MAR, henceforth), argues that spillovers are more likely to occur between regions with similar production specialization. Conversely, the diversification view put forward by Jacobs (1969) is that knowledge spillovers are enhanced by complementarities between firms. Taking this view, regions with diversified production should produce more innovations because complementary knowledge is what gives rise to increasing returns.

Our findings corroborate with past evidence on the important role of state's own R&D stock and human capital in producing new inventions at the state level. Results further underline the importance of external knowledge, via spatial interactions, which in some cases are more than half in size of state's own knowledge. Innovation activity, either from the input side (R&D and human capital) or from the output side (patents) performed in other states greatly contributes to a state's production of patents. The effect is stronger when we consider spatial influences from all states, in particular from the most innovative, and to a lesser extent from neighboring states. Finally, accounting for technological space along with geographic, we find that technological similarity, in particular similarity in technological specialization, has a nuance role in shaping knowledge spillovers, and therefore, we are in favor of the MAR approach.

Coordination of R&D innovation-friendly policies (e.g. R&D tax credits) or policies related to enhancing human capital (mobility of researchers, spending on education, personal taxes) among states, and not only among neighbors, is crucial so that the local production activity can reap off all potential benefits. Furthermore, as economic theories have already stressed, location greatly matters for innovation production. In recent years, the innovation landscape of the US has drastically shifted. Our descriptive analysis corroborates with the fact that states in the Eastern and Western Coasts along with some states around the Great Lakes have shot up in innovation activity eclipsing those from Midwest and Northeast, the traditional backbone of the American invention. Consequently, to fully benefit from technological spillovers, a firm should choose to locate its production of innovation to states which are either surrounded by states with good innovation performance or, even better, closer, if not continent, to a top innovator state. Similarity of states' technological specialization could further increase knowledge spillovers and boost innovation output potentials.

The remainder of the paper proceeds as follows. Section 2 presents the framework of our analysis and the data. Section 3 discusses the results. Section 4 summarizes our findings and concludes.

2. Methodology

2.1. A Spatial Knowledge Production Function

The starting point of our analysis 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.

Generation of new knowledge is described by the standard knowledge production function, introduced by Griliches (1979) and Jaffe (1986), which is is similar to the production of physical goods. The output of production of new knowledge (innovation), the innovative output, proxied by patents, is determined by knowledge inputs, R&D activity and human capital. In its basic form, is expressed as follows:

$$Q_{it} = \gamma(X_{it}) + X^* \tag{1}$$

where the vector Q represents a (logged) vector of NxT observations on N states innovation output across T time periods and i a given state (i=1,...,N). The explanatory variable vector X represents state level (logged) inputs to the innovation production process across states and time, with X reflecting observable/measurable state-own R&D ($R\&D$) and human capital (HC) inputs. Reasonably, we assume that there are unobservable/unmeasured inputs to the innovation production process arising from external and accessible to state i research activities.

It has become a stylized fact that empirical measures of variables associated with regional knowledge production such as X in equation (1) exhibit spatial dependence (Parent and LeSage, 2008). If both the measurable variable X included in equation (1) and the unmeasurable excluded variable X^* exhibit spatial dependence, then one can show that a spatial regression relationship will result.

Let spatial autoregressive processes govern spatial formation of observable and unobservable inputs, X and X^*, of the knowledge production process described by equations (2) and (3) below. One can introduce zero mean, constant variance disturbance terms u, v, ϵ, along with an NxN spatial weight matrix W, reflecting the connectivity structure of the states.

$$X = \zeta \tilde{W} X + u \tag{2}$$

where the scalar parameter ζ reflects the strength of spatial dependence in X and $u \sim N(0, \sigma_{u^2} Q_{NxT})$.

$$X^* = \delta \tilde{W} X^* + v \tag{3}$$

where the scalar parameter δ reflects the strength of spatial dependence in X^* and $v \sim N(0, \sigma_{v^2} Q_{NxT})$.

The error terms of the equations above are related as follows:

$$v = \rho u + \epsilon \tag{4}$$

where $\epsilon \sim N(0, \sigma_{\epsilon^2} Q_{NxT})$.

The condition $\rho \neq 0$ indicates that shocks u and v are correlated, which, in turn, implies correlation between included variables X and excluded variables X^*. An omitted variable that is correlated with inputs of 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.

Plugging the expressions in (2) and (3) back in (1) and following Pace and LeSage (2007) one obtains:

$$Q_{it} = \beta_0 + \beta_1 \tilde{W} Q_{it} + \beta_2 \tilde{W} Q_{i\,t-1} + \beta_3 X_{it} + \beta_4 \tilde{W} X_{it} + e_{it} \tag{5}$$

where Q is the innovative output of state i proxied by the number of patents, X is a vector of knowledge inputs, namely R&D stock ($R\&D$)and human capital (HC), which is proxied by the number of researchers, and e and i.i.d. error term.

Equation (5) represents what has been labeled a spatial Durbin model (SDM) by Anselin (1988). This model subsumes the spatial error model (SEM) as a special case when the parameter ρ = 0, indicating no correlation in shocks of measured and unmeasured regional inputs of the knowledge production process. Conventional omitted variables treatment considers the non-trivial case where correlation exists between included and excluded variables. It can be shown that even if ρ = 0, it would still be possible to reject the SEM model in favor of the SDM model. That is, ρ = 0 is a necessary but not sufficient condition for the SEM model. Consequently, 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.

The spatial aspect of the knowledge production specification is represented by a NxN (where N is the number of states) spatial weighted matrix, W, which captures the degree of linkages between state i and each one of the remaining states. Each generic element, w_{ij}, of the connectivity matrix is equal to the inverse of squared distance ($w_{ij} = 1/d^2$) between state i and state j (with $w_{ij} = 0$ when $i = j$), or equal to 1 for states that are closer than a pre-specified cut-off and 0 otherwise. In words, the innovation performance of a state i depends, along with state's innovation performance ($R\&D$, HC), on contemporaneous (WQ_{it}, $WR\&D_{it}$, WHC_{it}) and lagged (WQ_{it-1}) co-performances of innovation of the rest of the states.[2]

As expected, the innovation performance of a state will be more affected by some states than others, as expressed by the connectivity matrix. Note that the spatial lag refers to patenting activity in the pre-

[2]For more specifications of weight matrices, see Anselin et al. (1996).

vious year to mitigate endogeneity bias.[3] The disturbance term, ϵ_{it} can potentially itself exhibit spatial dependence, often of the following form: $e_{it} = \lambda \sum_{i \neq j} w_{ij} e_{jt} + v_i$, where v_i is iid error term.[4]

One can consider alternative specifications of the spatial weighted matrix, W, to test various hypotheses. For example, in considering the effect of innovation performance of six neighbor states, we keep only the bilateral distance weights between a given state, i, and each one of its six close neighbors, setting any bilateral distance between state i and each one of the remaining states equal to zero. Similarly, in considering the top innovator's effect on a states patent production, we keep only the bilateral distance weights between a state i and each one of the (10) innovation leaders, setting any other bilateral distance equal to zero.

States, however, located near each other may exchange more knowledge with each other simply because they have similar technological efforts and/or technology specialization of production structures. Not accounting for technological similarities (differences) may lead to an overestimation of the geography effect. Therefore, we also consider, along with the geographic proximity, technological proximity between states.

More specifically, technological effort distance between two states i and j for a given year, t, is proxied as[5]:

$$TechnologicalDistance = \mid ln \frac{R\&D_i}{Scientists_i} - ln \frac{R\&D_j}{Scientists_j} \mid$$

One would expect regions with high technological activity are also those with most intense knowledge exchange and spillovers .

Technological specialization closeness between two states i and j for a given year t is the (uncentered) correlation of their patent profiles and calculated as:[6]:

$$StructuralCloseness = \frac{sh_i' \; sh_j}{\sqrt{\sum_{s=1}^{37} sh_{is}^2 \sum_{s=1}^{37} sh_{js}^2}}$$

where, sh are shares of patents issued in a technology field (out of 37, in total, fields) in states i and j.

[3]The potential endogeneity bias arises because, while some states' innovation performance has an impact on state's i innovation activity, state i's activity may also have reverse impact on other states' innovation activity.

[4]Alternative error term structures are the spatial error component model, $e_j = \lambda \Sigma_{i \neq j} w_{ij} \xi_i + v_j$, and the spatial moving average model, $e_j = \lambda \Sigma_{i \neq j} w_{ij} e_i + v_j$, as discussed in Deltas and Karkalakos (2013).

[5]The level of technological capability of a region is often proxied in the literature (Peri, 2005) by the level of R&D activity and human capital (number of researchers). According to innovation-driven models of growth (Grossman and Helpman, 1991; Aghion and Howitt, 1997), R&D stimulates innovation and facilitates the imitation of others' discoveries. Apart from contributing directly to invention, human capital also accounts for aspects of innovation not captured by the R&D sector, including 'learning-by-doing' and 'on-the-job-training' (Romer, 1989; Redding, 1996).

[6]Structural proximity between two states is measured as in Jaffe (1986). We first classify each patent, according to their primary US Classification, in one of the 37 technology fields, as defined in Hall and Ziedonis (2001).[7] Then, for each state, we create a patent profile by taking the vector of shares of patents issued in technology field, $Sh_i = (sh_{i1}, sh_{i2}, ..., sh_{i37})$, for a given year.

The constructed index ranges from zero (minimum similarity), which implies that the production structures are orthogonal, to one (maximum similarity), which denotes identical sectoral structure (patenting in exactly the same sectors) in two states. Researchers are expected to benefit more from other researchers who work in the same or related sectors (Bode, 2004). Consequently, one expects to find a positive association between intensity of knowledge flows between two states specialized in similar sectors.

We can further test the role of technological proximity, along with the geographic, in shaping local production of patents. For example, in considering the effect of technological specialization similarity, we keep only the bilateral distance weights between a given state, i, and each one of its close in technological specialization states (if the correlation of patent profiles between two states is greater than the median 0.71 states are considered to be similar in technological specialization), setting any bilateral distance weights between state i and each one of the remaining states, which are dissimilar in technological specialization with state i, equal to zero. Similarly, in considering the technological effort similarity, we keep only the bilateral distance weights between a state i and each one of the similar in technological effort states (if the correlation between two states is greater than the median 0.52 then states considered to be similar in technological effort), setting any other bilateral distance weights between state i and each one of the rest of the dissimilar in technological effort states equal to zero.

Estimation

The dependent variable, the innovation output, is the count of patents granted to a state in year t. To transform the count data into continuous, we weight each patent by the number of patent citations, taking into account the grant year and the technology field of the patent. More specifically, every patent is assigned to an issued year and technology field. We have 14 years and 37 technology groups; therefore, each patent is classified in one out of 14x37=518 groups. Each patent in every group is then weighted by the number of citations it has in the group's distribution. The weighting scheme is $w_1 = 0.1$, if citation belongs to the 1st quintile, $w_2 = 0.2$ for the 2nd, $w_3 = 0.3$ for the 3rd, and $w_4 = 0.4$ for the fourth. We then sum these values up for every state at year t and get our weighted measure of innovation output. Applying this weighting scheme, the dependent variable, Q_{ij} is now continues as the rest of the variables.

In estimating equation (2), we follow Baltagi and Lui (2011), who have extended the instrumental variable estimators of Kelejian and Prucha (1998) and Lee (2003) proposed for the cross-sectional spatial autoregressive model to the random effects spatial autoregressive panel data model.

2.2. Data

Our empirical analysis is based on a sample of 50 US states (DC is excluded) from 1993 to 2006. Annual data are retrieved from the following sources:

Patent and citation data are obtained from the National Bureau of Economics Research (NBER) *Patent and Citation Data Project*, which is publicly available and described in detail by Hall and Ziedonis (2001).[8]. The database contains all utility patents granted by the US patent office since 1975 and all citations to these patents up until 2006. We choose the sample of patents granted between 1993 and 2006 whose assignee is located in the US.

Information on the two inputs of knowledge production function, R&D expenditure (for constructing R&D capital stocks) and doctoral scientists and engineers devoted to research (for human capital) is extracted from the National Science Foundation *Science and Engineering State Profiles*.[9] To calculate R&D (in million 2000 US dollars) stock, we use the perpetual inventory method as in Guellec and van Pottelsberghe de la Potterie (2004).[10]

Finally, the allocation of patents into different technological fields is based on patents' primary US Classifications according to the NBER.

Table 1 below provides the descriptive statistics of the variables included in our model:

Table 1: Summary Statistics

variables	Observations	Mean	St. Dev.	Min	Max
$Patents$	700	326.41	604.65	1.1	4956.30
$Scientists$	700	11.93	14.43	0.73	99.06
$R\&Dstock$	700	19.90	33.39	0.25	263.37
$TechnologicalDistance$	700	0.63	0.50	0	3
$StructuralCloseness$	700	0.70	0.18	0.05	1

Note: *Patent* are weighed by citations; *Scientists* are in thousands; *R&Dstock* in billions 2000 US dollars; and *TechnologicalDistance* and *StructuralCloseness* are constructed indices.

Each state, on average, produces about 327, weighted by their citations, patents, has 12 thousands scientists and accumulated technological knowledge of 20 billion US dollars value. The maximum value of all indices of innovation activity belong to the state of California (CA). In terms of technological effort, states, on average, appear to be less distant than the maximum potential distance that they could have and also quite close in terms of technological specialization in their productions.

Below, Figure 1 shows the production of patents (unweighted by their citations) in the US over the period 1993-2006. Intense innovation activity is concentrated in few states in the US (shown in bold). The highest by far production of patents takes place at California (CA) and then in the states of New York (NY),

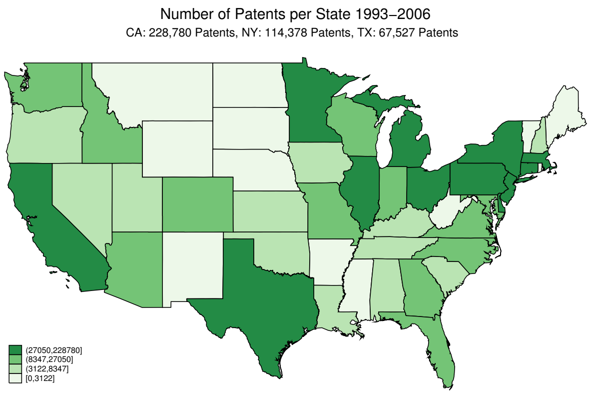
[8]The database is available at: http://sites.google.com/site/patentdataproject.

[9]Data extracted from the National Science Foundation database is given biannually. We use STATA's interpolation methods to fill in the gaps.

[10]Following the literature, we have tried different depreciation percentages, e.g., 15%, and 20%. The resulted R&D stocks are highly correlated.

and Texas (TX), among others. The least patent production takes place in the states of Alaska (AK), Hawaii (HI), the Dacotas (ND, SD), and Wyoming (WY).

Figure 1: Patent Production per State



Moreover, states which are patent production leaders have also the highest accumulated technological knowledge (R&D stock) and human capital (scientists) as Table A.1 in the Appendix shows. Similarly, laggers in patent production are also lower in the ranking in technological knowledge and scientists. More than half (about 70%) of the total US R&D activity in our sample is produced by ten states: California (CA), Massachusetts (MA), Michigan (MI), New Jersey (NJ), and New York, (NY), Texas (TX), Illinois (IL), Pennsylvania (PA), Maryland (MD), Washington (WA), and Ohio (OH), while the 30% of patents is produced by 40 states.

3. Empirical Results

Table 2 provides the results. Column (1) reports estimates of the standard knowledge production function specification without spatial effects, while columns (2)-(5) show estimates of specifications with spatial aspects. Specifically, column (2) displays spatial interactions from all states, from the side of innovation output - patents and column (3) from the side of knowledge inputs - R&D and human capital. Analogously, columns (4) and (5) report spatial interactions only from the very close neighbors.

As a benchmark, we begin by reporting, in column (1), estimates of a standard knowledge production function. Results confirm the importance of homegrown knowledge stock ($lnR\&D_t$) and human capital ($lnHC_t$) in the production of innovation. Both inputs of knowledge function have a positive and statistically significant effect. For example, an 1% increase of own $R\&D$ stock is associated with 0.95% increase of patent production, while an 1% increase in the number of scientists relates to 0.34% increase of innovation output.

Table 2: Estimates of Knowledge Production (All and Neighboring States)

		All States (50)[a]		*Nearby States*[b]	
	(1)	(2)	(3)	(4)	(5)
$lnR\&D_t$	0.952**	0.553**	0.436**	0.542**	0.745**
	(3.12)	(2.62)	(3.03)	(2.77)	(3.24)
$lnHC_t$	0.338**	0.293**	0.189**	0.199*	0.288**
	(4.32)	(4.51)	(2.02)	(1.83)	(2.72)
$W * lnQ_t$		0.461**		0.289**	
		(2.88)		(2.35)	
$W * lnQ_{t-1}$		0.228		0.105	
		(0.53)		(0.88)	
$W * lnRD_t$			0.108*		0.173*
			(1.85)		(1.91)
$W * lnHC_t$			0.075		0.083
			(0.64)		(1.04)
Constant	0.802**	0.528**	0.766**	0.986**	0.842**
	(2.91)	(3.19)	(5.24)	(2.23)	(4.11)
Time effects	yes	yes	yes	yes	yes
R-squared	0.68	0.71	0.70	0.73	0.72
obs	700	700	700	700	700

All columns report maximum likelihood (ML) estimates with spatial error dependence and time effects. Numbers in parentheses are t-values. (**) and (*): significance at 5% and 10% level, respectively.
[a] The generic element, w_{ij} equals to the inverse of squared distance between state i and state, j.
[b] The generic element, w_{ij} equals to the inverse of squared distance between state i and its neighboring state j (we consider 6 neighbors, j=1, 2, 3, 4, 5, & 6), 0 otherwise.

Results, however, appear to be somewhat different when we allow for spatial interactions in columns (2) and (3). Estimates show that not only own knowledge stock (R&D effort and human capital) matters, but also the co-performances of other states. Starting with the production of innovation (number of patents), external contemporaneous patent production in other states appears to largely influence local patent production. As the coefficient of $W * LogQ_t$ in column (2) indicates, an 1% increase of the patent production of other states is associated with an increase in the local production of patents by 0.46%; an effect as large as that of own R&D stock. An additional 0.23% increase takes place when the lagged value of patent production in other states ($W * LogQ_{t-1}$) is also included. However, the latter is statistically insignificant. Furthermore and with respect to the inputs of knowledge production, external knowledge, gained via other states' R&D stock and contacts of scientists, is positively associated with local patent production, as estimates in column (3) reveal. Therefore, knowledge spillovers, either from the output or input side of knowledge process, do shape the local production of patents.

Next, we want to explore whether spatial interactions originating from neighboring states have a stronger impact on local patent production compared to spatial interactions from all states ('average' state). As technological knowledge is highly contextual and requires frequent contacts and interactions to spill over, close neighboring could further enhance such spillovers. We, therefore, consider only spacial interactions from six neighboring states on state's *i* patent production. Columns (4) and (5) report such effects. As the estimates reveal, the effect of own R&D remains important and so does that of scientists, but the effect of patent co-performances of the nearby states is smaller then that of the 'average' state in column (2). As column (4) shows, an 1% increase in the contemporaneous production of patents of the surrounding states, increases local innovation production by 0.29%. There is also an additional effect of 0.11% from the past patent co-performances of the neighbors, but this effect is not statistically significant. However, neighboring seems to enhance more the spillovers from R&D efforts and contacts of scientists of the neighboring states compared to spillovers from the average state. In particular, local production of patents gains about two times more from R&D originating from the surrounding states than from R&D activity of all states as reported in column (2). Human capital of the close-by states appears to also have a slightly larger effect on local patent production than that of all states, but in both cases estimates are statistically insignificant. Consequently, geographic nearness significantly affects the size of the spillovers and their effects on local innovation production.

An oft-expressed view is that top innovator states, i.e., states that are big R&D spenders, no matter where they are located, affect local patent production. Arguably, technological leaders are expected to generate influential technological knowledge, which is wider in geographic scope compared to less technologically advanced states', which are mainly receivers of this knowledge and merely apply small variations or adjustment of it (Peri, 2005). Therefore, we want to examine whether the geographic scope of external accessible knowledge from the top innovator states has different implications on local patent production from the average state and the close neighbor state effects. Table 3 report the results. Columns (6) and (7) show that homegrown R&D stock and scientists pertain their important role in producing innovative output. In addition, patent co-performance of the top ten innovator states largely shapes the local patent production, and as column (6) shows and this effect is almost half in size of the effect of local own R&D stock. Further, as column (7) shows, the performance of R&D stock and scientists of the top innovation performers matters for the local patent production as their impact is not only positive, but also statistically significant.

Table 3: Estimates of Knowledge Production (Top Innovative States)

	Innovator States $(top\,10)^{a}$ (1)	(2)
$lnR\&D_t$	0.619**	0.674**
	(2.41)	(2.07)
$lnHC_t$	0.121*	0.242**
	(1.94)	(3.15)
$W * lnQ_t$	0.342**	
	(2.53)	
$W * lnQ_{t-1}$	0.121	
	(1.17)	
$W * lnR\&D_t$		0.092**
		(2.05)
$W * lnHC_t$		0.114*
		(1.81)
Constant	0.773**	0.903*
	(3.54)	(1.98)
Time dummies	Yes	Yes
R-squared	0,74	0,68
Obs	700	700

All columns report maximum likelihood (ML) estimates with spatial error dependence and time effects. Numbers in parentheses are t-values. (**) and (*): significance at 5% and 10% level, respectively.
[a] The generic element, w_{ij} equals to the inverse of squared distance between state i and state j, where state j is one of the Top 10 innovator states (California (CA), Massachusetts (MA), Michigan (MI), New Jersey (NJ), and New York, (NY), Texas (TX), Illinois (IL), Pennsylvania (PA), Maryland (MD), Washington (WA), and Ohio (OH)), 0 otherwise.

In sum, we find that there are important spatial effects, which shape local innovation production. External accessible knowledge from the average and top innovator state is found to have a larger influence on a state's patent activity than the neighbor's state effect. It appears that apart from geographic proximity, which is important for knowledge diffusion, the quality and the relevance of technological knowledge and researchers is also important for shaping local innovation production. The latter finding implies that states can exchange knowledge spillovers not only because of their geographic proximity, but also because of their technological proximity.

Our last exploration, therefore, involves the investigation of the role of technological nearness, along with geographic proximity, on local patent production. We approach states' technological nearness in two ways. First, by considering the similarity of technological specialization of states, i.e., whether states have patents in the same technological sectors, and second, by considering the similarity of in their technological efforts, i.e., states' proximity of R&D activity per scientist. Estimates are reported in columns (1)-(2) and (3)-(4), respectively, of Table 4. In columns (1) and (2), for each state we only consider the distance from states that have a similar technological specialization. Specifically, states where *StructuralCloseness* >= 0.71. This cutoff value represents the median in the distribution of pairs of states with respect to *StructuralCloseness*. Note that as the median is not 0.5 (see Summary Statistics in Table 1), the distribution is skewed to the right. In Columns 3 and 4, for each state we only consider the distance from states that have a similar technological effort. Specifically, states where *TechnologicalDistance* <=0.52. This cutoff value represents the median in the distribution of pairs of states with respect to *TechnologicalDistance*. Note that as the median is not 1.5 (see Summary Statistics in Table 1), the distribution is skewed to the left.

Table 4: Estimates of Knowledge Production (Technological Similarity)

	Technological Specialization[a]		*Technological Effort*[b]	
	(1)	(2)	(3)	(4)
$lnR\&D_t$	0.512**	0.584**	0.612*	0.704*
	(3.01)	(2.71)	(2.41)	(2.05)
$lnHC_t$	0.089*	0.097*	0.173*	0.144*
	(2.13)	(1.78)	(2.16)	(2.06)
$W * lnQ_t$	0.632*		0.184	
	(1.91)		(1.21)	
$W * lnQ_{t-1}$	0.005		0.019	
	(0.96)		(0.57)	
$W * lnR\&D_t$		0.057*		0.136*
		(2.02)		(2.47)
$W * lnHC_t$		0.177*		0.276*
		(2.34)		(1.88)
Constant	0.447*	0.773*	0.856*	0.984*
	(2.41)	(2.53)	(2.28)	(1.82)
Time dummies	Yes	Yes	Yes	Yes
R-squared	0,74	0,68	0,65	0,64
Obs	700	700	700	700

All columns report maximum likelihood (ML) estimates with spatial error dependence and time effects. Numbers in parentheses are *t*-values. (**) and (*): significance at 5% and 10% level, respectively.
[a] The generic element, w_{ij} equals to the inverse of squared distance between similar in technological specialization states i and j (if the correlation of patent profiles between two states is greater than the median 0.71 states are considered to be similar in technological specialization).
[b] The generic element, w_{ij} equals to the inverse of squared distance between similar in technological effort states i and j (if the correlation between two states is greater than the median 0.52 then states considered to be similar in technological effort)

As columns (1) and (2) show, the size and significance of state's own R&D and human capital is similar to what has been previously found. What is different, however, is that irrespective of geographic distance, state's local production of patents is greatly influenced from states with similar technological specialization. In other words, the co-performances of patent production of states with similar technological sector specialization as state's i have a strong positive effect on state's i patent production of 0.63% as the coefficient of $W * lnQ_t$ in column (1) indicates. Similarly, the co-performances of R&D and, in particular, of researchers of similar in technological specialization states with state *i*, positively affect the patent performance of state *i*, as it is shown in column (2). It appears that researchers are expected to benefit more from other researchers who work in the same or related technologies (Bode, 2004; Peri, 2005). Consequently, similar technological specialization enhances spatial knowledge diffusion.

Furthermore, as column (4) shows, the technological effort of the states also matters, along with geographic proximity, for knowledge spillovers. A state's production of patents is influenced from the co-performances of R&D and mainly of researchers' of states with similar technological effort as state's *i*. In contrast, the co-performances of patent productions of states, which pour similar technological effort as state *i*, do not necessarily affect state's *i* patent performance.

Overall, the inclusion of spatial interactions deflates the size of local homegrown R&D and human capital effect on local production of innovation. External accessible knowledge spillovers are also important for the local patent production. Our spatial knowledge production estimates of own R&D elasticity (44% - 75%) are in the vicinity of existing estimates reported in the international knowledge spillover literature, and in particular in the studies of Peri (2005) (60%-80%), Branstetter (2001) (72%), Pakes and Griliches (1980) (61%), and Bottazzi and Peri (2007) (78%). Geographic proximity is found to be important for knowledge spillovers, but technological similarity, in particular in technological specialization, has a nuance role in shaping knowledge spillovers. Evidence seems to corroborate with the view proposed by Marshall-Arrow-Romer, who argue that spillovers are more likely to occur between states with similar technological specialization, which share common technological knowledge and pour similar technological effort.

4. Conclusion

Innovation policies affect the distribution of innovation activity in a country and, therefore, technological knowledge interaction between two regions is also influenced by innovation activity performed elsewhere. In this paper, we augment the standard knowledge production function with spatial structure to account for spatial interactions in the local production of innovation. By doing so, we seek to develop our understanding of the diffuse nature of technological externalities in geographical and technological space.

Using a panel data set of 50 states over the period from 1992 to 2000 for the US, our findings strongly support the significant contribution of state's own technological knowledge and human capital in producing new inventions at the state level. Our evidence further points to the importance of external knowledge via spatial interactions, which in some cases are more than half in size of the state's own R&D effect. The patenting performance as well as the level knowledge stock and scientists of other states strongly affect a state's production of patents; however, the effect of external patenting performance is larger compared to that of external R&D and scientists' interactions. Specifically, we find that local innovation production benefits mostly from external innovation activity performance originating from all and top innovator states, and to a lesser degree from near-by states' performances. Finally, accounting for technological space along with geographic, we find that technological similarity, in particular similarity in technological specialization, has a nuance role in shaping knowledge spillovers.

Future research could shed more light from firm-level data, which would allow a more detailed investigation of technological space and the specialization hypothesis. However, our evidence still has policy relevance. Local innovation activity, in terms of producing patents, reaps off significant gains from technological specialization similarities across states in the US and geographic location. Most of the top innovator states in the US lie on the West and East Coasts, with a couple of hubs around the Great Lakes, while the least innovative states are found to be located in the Midwest and South. As our results have shown, firms, located a in state, benefit from spillover effects from other firms located in neighboring states, but mainly from firms located in the most innovative states. Therefore, firms can boost their innovation output potentials by tapping into regional (state) characteristics and interacting with similar in technological specialization firms.

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Appendix

Table A.1: Summary Statistics per State

State	Patents		Scientists		R&Dstock		R&Dspending	
	mean	st. dev.	mean	st. dev.	mean	st. dev.	mean	st. dev.
AK	6.77	3.08	1.30	0.09	0.83	0.19	0.20	0.06
AL	51.06	16.26	7.11	1.19	10.23	0.56	2.15	0.33
AR	28.11	10.64	3.13	0.43	1.78	0.23	0.40	0.06
AZ	142.19	43.32	7.74	1.20	12.16	3.98	3.07	1.05
CA	3603.81	1126.58	84.56	10.10	210.66	33.46	48.14	7.72
CO	219.18	63.58	13.12	1.66	17.91	3.07	4.14	0.78
CT	491.23	125.84	10.26	1.15	19.88	6.06	5.12	1.68
DE	401.25	91.19	3.92	0.44	7.21	0.70	1.50	0.40
FL	406.21	136.85	17.48	2.12	21.80	2.36	4.81	0.61
GA	178.34	50.39	12.18	1.71	11.36	3.13	2.81	0.73
HI	12.03	4.60	2.79	0.28	1.93	0.14	0.40	0.09
IA	98.41	30.31	4.92	0.29	5.44	0.64	1.22	0.21
ID	260.54	155.66	2.50	0.36	4.21	1.31	1.01	0.31
IL	930.89	236.86	23.69	1.45	42.80	6.77	9.70	1.56
IN	203.88	68.63	9.66	0.85	15.49	2.55	3.61	0.78
KS	56.33	11.33	4.31	0.37	4.97	2.39	1.40	0.58
KY	63.21	20.58	4.91	0.52	3.20	0.97	0.81	0.23
LA	64.97	25.06	5.94	0.23	2.86	0.54	0.66	0.16
MA	682.09	162.51	29.14	3.81	57.52	8.13	13.11	2.07
MD	178.13	49.24	25.26	3.30	41.45	4.84	9.26	1.88
ME	20.29	6.37	2.46	0.13	1.03	0.43	0.28	0.11
MI	796.50	184.39	17.65	1.54	69.23	9.63	15.26	2.35
MN	528.39	136.16	11.42	1.36	18.44	3.82	4.40	1.06
MO	158.23	46.13	9.80	0.53	10.71	1.36	2.43	0.41
MS	21.82	8.48	3.38	0.23	2.16	0.76	0.55	0.28
MT	21.09	6.99	1.98	0.19	0.69	0.25	0.18	0.06
NC	231.53	80.87	17.31	2.47	19.40	5.13	4.79	1.23
ND	8.62	3.34	1.63	0.46	0.72	0.36	0.20	0.12
NE	33.54	9.93	2.97	0.11	1.92	0.53	0.48	0.16
NH	72.53	18.31	2.66	0.36	4.00	1.72	1.11	0.46
NJ	873.65	246.29	23.38	1.92	53.51	4.67	11.59	1.18
NM	47.02	17.28	8.44	0.79	16.34	2.43	3.75	0.74
NV	86.51	37.16	2.11	0.33	1.79	0.57	0.46	0.14
NY	1702.38	412.93	45.88	2.40	63.77	2.05	12.86	0.89
OH	665.43	198.04	21.68	1.76	35.75	1.63	7.39	0.65
OK	90.42	25.43	4.96	0.24	3.08	0.32	0.67	0.10
OR	129.94	29.54	8.12	1.13	7.51	3.72	2.14	1.00
PA	530.06	130.86	28.08	2.48	45.87	2.18	9.58	0.92
RI	39.77	10.40	2.87	0.32	5.03	2.13	1.35	0.48
SC	81.71	23.29	5.50	0.48	4.83	1.31	1.22	0.37
SD	10.69	6.18	1.14	0.06	0.36	0.11	0.09	0.04
TN	120.13	38.50	9.61	0.69	8.84	2.40	2.18	0.57
TX	1001.86	234.42	34.72	3.51	47.63	10.75	11.39	2.42
UT	106.51	31.54	5.33	0.45	5.54	1.35	1.34	0.29
VA	194.44	48.92	19.47	2.85	20.97	6.08	5.35	1.60
VT	15.89	4.53	1.91	0.20	1.79	0.18	0.39	0.08
WA	337.48	93.70	15.55	2.21	36.15	8.42	8.67	2.01
WI	296.01	73.57	9.23	0.87	11.87	2.21	2.77	0.54
WV	10.94	3.99	2.28	0.19	1.92	0.35	0.44	0.07
WY	8.28	3.37	0.89	0.09	0.36	0.04	0.08	0.02

Note: First column is state' two-letter abbreviation; *Patent* are weighed by citations; *Scientists* are in thousands; *R&Dstock* and *R&Dspending* are in billions 2000 US dollars.