An examination of the role of local and distant knowledge spillovers on the US regional knowledge creation

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ABSTRACT: This paper examines the role of academic *and* private R&D spending in the frame of a knowledge production function estimated across 3,109 US counties. We distinguish the role of local, face-to-face, knowledge spillovers that are determined by geographical proximity from distant spillovers captured by a matrix of patent creation-citation flows. The advantage of the latter matrix is its capacity to capture the direction of the spillovers. We control for the spatial heterogeneity between metropolitan and non-metropolitan counties as well as between states. Our empirical results show that spillovers due to private knowledge contribute to higher returns in metropolitan counties than in non-metropolitan regions. On the other hand, knowledge created in the academia leads to spillovers displaying spatially homogeneous returns. Our results imply that future innovation policies need to grasp more fully the role of distant knowledge spillovers, especially those generated in the academia, and recognize better the presence of heterogeneity in the sources and location of knowledge creation.

Keywords: Knowledge production function, knowledge spillovers, patent citation flows, spatial econometrics

JEL classifications: C21, O18, O31, R11

Introduction

Innovation and technological change are important sources of economic growth (Audretsch and Feldman 1996). The literature that investigates their creation has mostly focused at the firm level (Jaffe 1986; Blundell et al. 1995; Cincera 1997; Gurmu and Perez-Sebastian 2008) in the framework of a knowledge production function à la Griliches (1979). Since the contribution of Jaffe (1989), many studies have recognized knowledge spillovers in a region, thereby shifting the unit of observation from the firm level to a geographical unit (Audretsch and Feldman 2004). However, even in the latter case, the empirical identification and measurement of knowledge spillovers is still a challenge.

Traditionally, knowledge spillovers have been assumed to be localized (Moreno and Miguélez 2012). Since all new knowledge produced cannot be appropriated totally, and non-appropriable knowledge has the properties of public goods, neighbors of a knowledge source can access new knowledge via face-to-face interactions based on close proximity (Jaffe 1986; Jaffe et al. 1993; Audretsch and Feldman 1996; Rodríguez-Pose 2001; Sonn and Storper 2008). However, empirical evidence suggests that knowledge spillovers may well reach beyond the boundaries of the locality under study. For instance, Anselin et al. (1997) find that the spillovers of university research flow across nearby regions. Since the previous contribution, several studies have used spatial econometric techniques to model and measure interregional knowledge spillovers (Anselin et al. 2000; Bode 2004; Parent and LeSage 2008; Autant-Bernard and LeSage 2011). These studies assume that all spillovers are measured by the geographical proximity embedded in the definition of a spatial weight matrix. But this is a somewhat unrealistic assumption to make considering that knowledge flows are not limited by physical vicinity. For instance, several studies on biotech firms have demonstrated that the knowledge sources that contribute to a firm's innovation can be distant (Gertler and Levitte 2005; Gittelman 2007).

In addition, the traditional distance-based weight matrix does not account for the *direction* of the flows. These two issues have motivated several contributions to base the measurement of knowledge externalities on patent citation data. Johnson et al. (2006) and Sonn and Storper (2008) explore the geographical patterns of local and distant knowledge flows while Maurseth and Verspagen (2002), Fischer et al. (2006) and Maggioni et al. (2010) investigate econometrically the factors at the origin of knowledge spillovers based on patent citation data. Mancusi (2008) does it too but across OECD countries instead of regional economies. However, to our knowledge, only Peri (2005) and Ponds et al. (2010) have measured distant knowledge spillovers with a patent creation-citation matrix and a patent co-publication matrix respectively in a regional knowledge production function. The former contribution focuses on the regions of Western Europe as well as on the US states and Canadian provinces for the period of 1975-1996. While Peri (2005) relies on USPTO data to capture knowledge spillovers, like we do, we offer a county-level approach that provides more details about these flows and we update the analysis to a more recent period. Ponds et al. (2010) focus on the regions of the Netherlands and measure knowledge flows as evidence of interregional collaboration between industry and the academia. However, none of the previous two contributions deal simultaneously with both private sector *and* university-induced knowledge spillovers in their model. Also, they disregard the possible overlap between localized and distant knowledge spillovers, which could lead to double counting. We remedy to these problems in this paper.

In addition, although many spatial econometric studies focus on interregional knowledge spillovers (Anselin et al. 1997; Bode 2004), the role of intra-regional spillovers is rarely explicitly explored in the literature. Their level depends on a set of cultural, institutional, and economic conditions such as the region's sectoral specialization or diversity (Feldman and Audretsch 1999; Karlsson and Gråsjö 2014), close links between business, academic, and government sectors (Asheim and Isaksen 2002; Asheim and Coenen 2005; Greunz 2005) among others. In order to avoid hand-picking some regional characteristics to control for intra-regional spillovers, we examine their role explicitly by relying on within-region patent citation flows and remedy to a significant gap in the literature.

Given the aforementioned background, the object of the current paper is to examine the role of localized and distant knowledge spillovers on knowledge creation. For this purpose, we adopt a knowledge production function at the US county level. Previous contributions on the US usually use states and Metropolitan Statistical Areas (MSA) as the unit of observations (Anselin et al. 1997; Anselin et al. 2000; Peri 2005; Ó hUallacháin and Leslie 2007). However, states are too broad to measure localized knowledge spillovers (Audretsch and Feldman 2004) and solely working with MSAs results in a sample selection bias due to the omission of non-MSA regions. In addition, not all innovation takes place in MSAs. By using county-level data, this paper better reflects the role of localized knowledge spillovers and the large size of our sample allows us to investigate how our results vary between metropolitan and non-metropolitan counties. Compared to previous papers, this approach provides the opportunity to draw more accurate innovation policies.

The remainder of the paper is composed as follows: Section 2 reviews the literature focusing on innovation and spatial knowledge spillovers. Section 3 describes our knowledge production function, its associated knowledge spillovers and presents the sources of our data.

The estimation results and their interpretation are reported in Section 4 while the last section closes the paper with concluding remarks.

Literature Review

Sources of Knowledge Spillovers

Theoretically, knowledge spillovers are understood as localized phenomena and their intensity is assumed to depend on the degree of local specialization and diversity (Audretsch and Feldman 2004). Specialization allows firms to lower their transaction costs and facilitate communication between them due to Marshall-Arrow-Romer externalities (Marshall 1920; Arrow 1962; Romer 1986). As such, industrial specialization in a region promotes knowledge spillovers across nearby firms (Glaeser et al. 1992). On the other hand, Jacobs (1969) points out that diversity also plays an important role. Exchanging knowledge between firms and agents from various industries can complement their respective knowledge and lead to synergistic activities across industries, thereby promoting knowledge spillovers à la Jacobs. Thus, higher diversity of industries in a region is beneficial to promote innovative activities. Although these two processes rely on opposite levels of regional specialization, geographical proximity across firms is the essence of knowledge spillovers in both cases.

However, if firms located nearby were to interact with each other only and combine local knowledge exclusively, the value of local knowledge would depreciate and eventually become useless (Moreno and Miguélez 2012). As a result, the region would become less innovative. For this reason, firms are continually searching for external knowledge sources outside of their local knowledge pool (Rosenkopf and Almeida 2003). Trippl et al. (2009) provide evidence that external sources of knowledge are important in the Vienna software clusters. The case study of Asheim and Isaksen (2002) also finds that external contacts are important in the innovation process of Norwegian shipbuilding, mechanical engineering, and electronics industries. Gertler and Levitte (2005) demonstrate the role of distant knowledge sources in biotechnology innovation. Therefore, the sources of knowledge spillovers are not only limited to geographically close clusters, but also include distant actors. By developing global pipelines to benefit from remote knowledge sources, firms can stimulate knowledge flows and generate innovation growth (Maskell et al. 2006).

Empirical Studies on the Extent of Knowledge Spillovers

Although the sources of knowledge spillovers can come from geographically remote partners as well as from partners clustered locally, most empirical studies define the extent of knowledge spillovers on geographical proximity. Jaffe (1989) is the first to have shifted the observation unit of the knowledge production function from the firm level to the geographical unit (Audretsch and Feldman 2004). He measures the coincidence between the location of a university and of industrial research activities within a state and uses his measurement as a proxy for knowledge spillovers due to academic research. His estimation results provide evidence of the existence of geographically mediated spillover, though their significance varies across technical areas. To our knowledge, Anselin et al. (1997) is the first empirical study that examines the existence of spillovers across US county boundaries. Based on spatial interaction theory, they use spatial econometric techniques to model interregional spillovers with various distance cut-offs. Their results show strong evidence of local spillovers of university research and private R&D across counties located within the same state or MSA. A few years later, Anselin et al. (2000) extend their previous work by relying on Lagrange Multiplier tests (Anselin et al. 1996) to decide whether spillovers should be modeled in the frame of a spatial lag model, where the dependent variable (knowledge output) is spatially lagged, or only through the spatial lag of university research and private R&D as done in Anselin et al. (1997). The results indicate that knowledge created within 50 miles and 75 miles from any MSA center plays a statistically significant role on the MSA's innovation level.

The spatial econometric study by Bode (2004) focuses on innovation across European regions. Based on the regions of western Germany, he models interregional knowledge spillovers using the spatial lag of the innovation output as well as of R&D employment, and checks the robustness of his results to several definitions of a spatial weight matrix. Some are distance-based weight matrices (with a distance cut-off or k-nearest neighbors number) while others are contiguity-based. The idea is to circumvent the lack of precise knowledge on the actual spatial extent of spillovers. Overall the results indicate the significant presence of knowledge spillovers, however their magnitude varies with the weight matrix and the knowledge spillover variables. More recently, Autant-Bernard and LeSage (2011) examine knowledge spillovers across French metropolitan areas. They consider private and public R&D inputs across 11 industrial sectors. Compared to previous works, their main contribution consists in providing the average direct and indirect effects of their spatial model (a spatial Durbin model) following the decomposition method brought to the fore by LeSage and Pace (2009). Their results indicate that both effects are significant, i.e. public and private investments in R&D in one locality will promote innovation locally (direct effect) as well as in other localities (indirect effects or spillovers).

Whether focusing on Europe or the US, all aforementioned studies rely on geographical proximity for their definition of the catchment area of knowledge spillovers, yet empirical evidence shows that proximity is not the only element at the origin of knowledge spillovers (Gertler and Levitte 2005; Gittelman 2007; Trippl et al. 2009). As a result, Parent and LeSage (2008) re-explore the definition of potential technological proximity defined by Jaffe (1989) and put an emphasis on the idea that (European) regions with similar research activity and production technology would better absorb the knowledge of their technological partners. The level of regional technological similarity they measure provides a weighting scheme that they apply on various spatial weight matrix specifications based on geographical proximity as well as transportation or technological proximity. The latter definition is innovative in the sense that proximity can be asymmetric within any pair of regions and proves statistically to improve the model fit compared to other matrix specifications. However, their approach does not directly measure the role of actual spillovers on knowledge creation because they rely on a proxy of actual knowledge flows and choose to model spatial dependence solely through spatially structured random effects.

In the regional knowledge production function literature, few studies pay close attention to distant knowledge spillovers. Exceptions include Peri (2005) who models distant knowledge spillovers based on patent citation across 147 subnational regions of western Europe and North America. Ponds et al. (2010) track how universities and private companies located in different regions of the Netherlands collaborate and file patents. Modeling distant knowledge flows based on patent citation patterns is mainly seen in the spatial interaction literature (Maurseth and Verspagen 2002; Fischer et al. 2006; Maggioni et al. 2010). Its results conclude that interregional knowledge flows not only depend on geographical proximity but also on technological proximity.

In addition, regional knowledge production studies rarely specify the level of intra-regional knowledge spillovers as an input variable. They control for several region-specific conditions such as sectoral specialization or diversity that can be at the origin of intra-regional knowledge spillovers (Feldman and Audretsch 1999; Karlsson and Gråsjö 2014) but so do several other variables. Examples seen in the literature include, among others, close links between actors of innovation (Greunz 2005) and the regional culture and institutional environment (Asheim and Isaksen 2002; Asheim and Coenen 2005). The Netherlands Organization for Applied Scientific Research (TNO) and the Fraunhofer Institute in Germany are examples of investments aiming at developing intra-regional spillovers (Ponds et al. 2010). Instead of hand-picking regional characteristics controlling for intra-regional knowledge spillovers, we prefer to model them directly through the level of intra-regional citation flows.

Empirical Model and Data

Regional Knowledge Production Function

Our starting point is the knowledge production function framework as defined in Griliches (1979). It assumes that a Cobb-Douglas functional form fits the relationship between innovation output and inputs. Since we adopt a regional knowledge production at the US county-level, input and output variables are aggregated values by county. Our sample is composed of the 3,109 continental US counties as defined in the 2000 US Census. We exclude the counties of Alaska, Hawaii, and of other islands because of their remoteness.

As a proxy for innovation output, we use the total number of utility patent applications averaged over 2003-2005 (***Patent***). The advantage of averaging over 3 years is to mitigate the effects of annual fluctuations in patent applications (Ó hUallacháin and Leslie 2007). Previous studies adopt the number of granted utility patents (Bode 2004; Parent and LeSage 2008; Autant-Bernard and LeSage 2011), but we prefer the patent applications as in Cincera (1997) and Ramani et al. (2008). Since grants often take years of review before an award is made, the year when the application for a patent is made is closer to the time knowledge is created, i.e. when innovation takes place. In addition, the average time lag between application and award can vary from one technology to the other. Since we focus on all technologies rather than a specific one, patent applications are a better proxy for innovation output in our case. Patent application data comes from the US Patent and Trademark Office (USPTO 2010). The dataset has been used by Jaffe and Lerner (2004), Crescenzi et al. (2007), and Sonn and Park (2011).

In order to allocate patent applications geographically, the addresses of patent assignees or patent inventors are available; however, both types of addresses have their own shortcomings. Since patents of a large company are filed by the headquarter of the company (Fischer and Varga 2006), using the address of an assignee may cause a biased geographical distribution of knowledge creation. The addresses of inventors tell us where they live but not whether they commute to another county to work. Although both options present a potential geographical mismatch, we believe the former may lead to a more serious bias because the majority of patents are filed by large companies. For this reason, we use the inventor's address for the geographical allocation of patents, and since a patent is usually credited to several inventors, we rely on the fractional counting method suggested by Jaffe et al. (1993) to allocate patents geographically. For instance, for any one patent with N inventors, 1/N fraction of the patent is allocated to each inventor. Then, the fractional patents are aggregated by county according to where the inventors are located so that they lead to rational, not integer, numbers. Finally, we use geocoding to match each inventor to one of the US continental counties based on the 2000 US Census. As a result, the level of knowledge creation in each county *i* is modeled as follows:

$$ln\boldsymbol{Patent_i} = \beta_0 + \beta_1 ln\boldsymbol{Private_i} + \beta_2 ln\boldsymbol{Univ_i} + \beta_3 ln\boldsymbol{Graduate_i} + \beta_4 ln\boldsymbol{Diversity_i} + \beta_5 ln\boldsymbol{Large_i} + \beta_6 ln\boldsymbol{Intra_i} + \beta_7 \ln \boldsymbol{Local.Private_i} + \beta_8 \ln \boldsymbol{Local.Univ_i} + \beta_9 ln\boldsymbol{Distant.Private_i} + \beta_{10} ln\boldsymbol{Distant.Univ_i} + \beta_{11} ln\boldsymbol{Size_i} + \sum_{i=1}^{48} \delta_i \boldsymbol{State}_i + \boldsymbol{\varepsilon_i} \quad (1)$$

The stock of knowledge is one of the principal determinants of knowledge production. Traditionally in the literature, the current level of knowledge stock is approximated by lag polynomials of R&D expenditures (Griliches 1979). But since R&D expenditures take time to produce any innovational output and they depreciate over time (Griliches 1992), the stock of knowledge is often calculated on past R&D expenditures by using the perpetual inventory method coupled with a pre-defined annual depreciation rate (e.g. Hollanders and ter Weel 2002; Hu et al. 2005; Klaassen et al. 2005; Mancusi 2008). Private and university research laboratories are the main institution of innovation, as such we specify the private and academic knowledge stocks separately. This classification is commonly used in the literature, especially in the US (Anselin et al. 1997; Acs et al. 2002; Ó hUallacháin and Leslie 2007). When it comes to the average annual depreciation rate of knowledge stock, Fischer et al. (2009) use 12% while Hollanders and ter Weel (2002), Hu et al. (2005), Okubo et al. (2006), and Mancusi (2008) adopt 15%. Here we also use a 15% depreciation rate.[1] One implication is that R&D expenditures have less than 1% of their original values after a period of eight years. Another motivation for the time difference between R&D investment and new knowledge creation is the alleviation of the potential endogeneity of such investments (Ó hUallacháin and Leslie 2007). As a result, we estimate the models with inputs measured in 2000, which corresponds to the most recent complete survey across US counties before 2003, and R&D expenditures lagged up to eight years in the past, i.e. 1995-2002. Before applying the perpetual inventory method, R&D expenditures are expressed in their 2003 dollar values using the Producer Price Index of the US Bureau of Labor Statistics.

The private expenditure data (***Private***) comes from Standard and Poor's COMPUSTAT database which provides annual and monthly data for more than 14,650 active U.S. and Canadian companies (Standard and Poor’s, 2001). COMPUSTAT draws its R&D data from the documents of the Securities & Exchange Commission among other sources. We extract the R&D expenditures from COMPUSTAT for each fiscal year and allocate each company’s location to a county, so that private R&D expenditures can be distributed across counties. We should note that COMPUSTAT presents some shortcomings. Since it relies on information from the Securities & Exchange Commission, R&D expenditures of undocumented small companies, such as venture capitals, are not reflected in the defined variable of the current study. As such the level of R&D expenditures reported in some counties may be biased downward; however, it is the only available measure of county-level R&D expenditures to our knowledge and the same data and issues have been reported in Crescenzi et al. (2007) at the MSA-level.

We collect the academic R&D expenditures (***Univ***) from the NSF Survey of R&D expenditures at universities and colleges. This data includes all academic R&D expenditures over $150,000 in each institution’s fiscal year. It covers all US universities and colleges granting a bachelor’s degree or higher in science or engineering as well as science and engineering doctorate-granting institutions and historically black colleges (National Center for Science and Engineering Statistics 2013). We allocate the academic R&D expenditures across counties based on the address of these academic institutions.

In addition to the knowledge stock variables, we specify several region-specific conditions. It is undeniable that the human capital acts as an input in the knowledge production function (Audretsch and Feldman 2004) and the positive impact of education on knowledge creation has been widely documented in the literature (Audretsch and Feldman 1996; Simon and Nardinelli 2002; Crescenzi et al. 2007; Storper and Scott 2009). As a result, we control for the level of human capital by relying on the share of the local population 25 years and over with a Graduate or professional degree from the 2000 US Census. (***Graduate***).

In the literature, there is a continuous debate about whether Jacobs externalities (Jacobs 1969) or Marshall-Arrow-Romer externalities (Marshall 1920; Arrow 1962; Romer 1986), in other words diversity vs. specialization, matter the most for the creation of economic knowledge. Glaeser et al. (1992) and Fung and Chow (2002) are in favor of diversity, but Jaffe (1986) and Henderson (2003) support specialization. In order to control for the relative level of diversity or specialization in a county, we use an index variable of the relative sectoral diversity of employment in each county (***Diversity***). Formally, our indicator is the index proposed by Duranton and Puga (2000) that we report in Equation (2) below. S_{ij} represents the share of employment of industry j in county i, while S_j is the share of industry j in national employment. The variable is calculated on the basis of employment classified across the 13 industry system developed for the 2000 US Census.

$$Diversity_i = 1/\sum_j \left| s_{ij} - s_j \right| \tag{2}$$

According to Anselin et al. (1997), smaller firms are more likely to be innovative than larger ones. Large firms spend huge amounts in R&D and exploit created knowledge in their own laboratories. In addition, since large firms have a larger influence on the local labor pool (Acs and Armington 2004), the level of agglomeration and ultimately of economic knowledge that results from their presence may be greater. Contrastingly, small firms spend relatively small R&D investment, but they have a comparative advantage with respect to exploiting knowledge spillovers from public institutes such as university laboratories (Acs et al. 1994). Thus small firms could be more efficient at innovating than large firms. In order to shed light on the actual influence of firm size on innovation, we measure the share of firms with at least 500 employees (***Large***)[2]. Relevant data come from the 2000 County Business Patterns. Last but not least, we control for the differences in the economic size of the US counties by including their number of employees (***Size***) as in Bode (2004).

Knowledge Spillovers

The literature recognizes knowledge spillovers as another important factor at the origin of knowledge creation (Jaffe et al. 1993; Audretsch and Feldman 1996). However, most empirical studies rely on proximity-based interregional knowledge spillovers only (Anselin et al. 1997; Anselin et al. 2000; Bode 2004; Autant-Bernard and LeSage 2011). We use a similar specification in this paper but we complement it with distant interregional knowledge spillovers and intra-regional knowledge spillovers. One common concern is whether contemporary or past patents should be used as a proxy variable for interregional knowledge spillovers (Bode 2004, 47-49). If we assume knowledge diffusion takes a short time, contemporary patents could be used as knowledge spillovers, hence leading to a spatial lag model (LeSage and Pace 2009). However, since our data is aggregated over all technologies of which speed of knowledge diffusion varies, the assumption of rapid knowledge diffusion proxied by contemporary patents may be too strong. Alternatively, building knowledge spillovers on past patents leads to biased estimates because of endogeneity as pointed out by Bode (2004). For these reasons, we find it more appropriate to use the neighbor regions' knowledge stock (the sum of depreciated R&D expenditures over 8 years) as a proxy for knowledge spillovers.

Localized interregional knowledge spillovers are based on geographical proximity. They represent the diffusion of tacit knowledge between researchers that takes place through face-to-face interactions (Bode 2004). As such a certain distance cut-off based on regular commuting patterns is often used to specify the spatial extent of face-to-face interactions. Anselin et al. (1997, 431) and Acs et al. (2002, 1076) choose 50 and 75 miles based on the US commuting patterns and test whether their results are sensitive to the cut-offs.[3] We adopt this approach here and use, in addition, an inverse exponential decay function to reflect that as distance between researchers increases, the intensity of interactions weakens because commuting costs go up. After setting various distance decay parameters, we chose the value 0.17 because it provides the best model fit.[4] Equation (3) presents the formula of localized spillovers of private knowledge stock. In the Equation, $1(\cdot)$ denotes the indicator function and $d(i,j)$ means the great circle distance between county i and j. The same formulation is applied to localized spillovers of academic knowledge stock.

$$\boldsymbol{Local.Private_i} = \sum_{j \neq i} W_{ij} \cdot Private_j \cdot 1(d(i,j) \leq 50\ miles) \ \ where\ W_{ij} = exp\big(-0.17 \cdot d(i,j)\big) \quad (3)$$

Face-to-face interactions may be the best channel to diffuse tacit knowledge in the physical vicinity delimited by commuting patterns, but previous empirical studies show that geographical proximity is not the only element at the origin of knowledge spillovers (Gertler and Levitte 2005; Gittelman 2007; Trippl et al. 2009; Ponds et al. 2010). More precisely, the spatial interaction modeling literature based on patent citation patterns (Maurseth and Verspagen 2002; Fischer et al. 2006; Maggioni et al. 2010) shows that interregional knowledge flows also depend on technological proximity. In order to shed light on the role of distant interregional knowledge spillover, we define a matrix of actual patent creation–citation flows.

In order to construct this matrix, we rely on "The NBER US Patent Citation Data File" (Hall et al. 2001). It contains information about any utility patents granted between 1963 and 1999 and reports the name of the 2,144,352 inventors as well as their respective addresses. A geocoding process was used to allocate patents across counties. More importantly, the database reports the citation records associated to each patent for the period of 1975 to 1999. It allows us to build a matrix that clearly stipulates the directionality of the spillovers which distance-based weight matrices cannot depict.

Since our innovation output variable is calculated over the years 2003-2005, the citation flows of the 1970s and 1980s are too outdated to lead to knowledge creation in the 2000s. In addition, as for local R&D expenditure (see above), knowledge stock generated elsewhere depreciates over time. With a 15% depreciation rate it implies that less than 1% of the original value of knowledge remains after eight years. As such, we only use the citation flows from 1995-1999 to make sure that the time difference between patents granted elsewhere (in the year 1995) and local patent applications (in the year 2003) is no more than eight years. The year of 1999 is the last year available in "The NBER US Patent Citation Data File". The time difference also helps alleviate potential endogeneity problems.

We use the fractional counting method proposed by Jaffe et al. (1993) and Sonn and Storper (2008) to allocate these flows across counties of origin and destination. For example, a patent with D inventors citing another patent (previously) deposited by O inventors leads to (D×O) flows of information, each of which records 1/(D×O) fraction of the patent. Once these fractional flows are aggregated at the county-level, they represent (3,109×3,109) patent citation flows that we denote the P matrix. Figure 1 shows the flows of patent cited in Californian counties based on the P matrix. We show one state only as the figure would not be readable otherwise. The dots are the centroids of the counties. The grey and black lines represent the origin, destination and frequency of the patents cited by Californian counties. Darker lines indicate more frequent citations. This figure evidently shows the most important knowledge flows come from counties located in distant states.

[FIGURE 1]

Since we use the patent citation flows as the weighting element for the knowledge stock of "partner" regions, the share of patent flows from a knowledge creating county *j* to a knowledge receiving county *i* is used as presented in Equation (4). In the equation, P_{ij} denote the (i^{th}, j^{th}) element of the P matrix (i.e. the frequency of citations that flow from county *j* to *i*) and M_{ij} is calculated by dividing P_{ij} by column sums of the P matrix. Using column standardization of the P matrix, we assume that a fixed portion of created knowledge in county *j* spills over to county *i*. As such, the distant knowledge spillover variables is interpreted as the (expected) aggregated amount of knowledge imported from distant partner regions to a knowledge receiving region *i*. Since the localized spillover variables captures all knowledge spillovers within 50 or 75 miles, we only count the distant spillovers that are taking place beyond 50 or 75 miles.

$$\boldsymbol{Distant.Private_i} = \sum_{j \neq i} M_{ij} \cdot Private_j \cdot 1(d(i,j) > 50\ miles)\ \ where\ M_{ij} = P_{ij} / \sum_i P_{ij} \quad (4)$$

Finally, when it comes to the level of intra-regional knowledge spillovers, we rely on the share of patent flows as above. However, it is only for flows within the same county, i.e. $\boldsymbol{Intra_i} = P_{ii} / \sum_r P_{ri}$. The level of intra-regional spillovers is measured separately from the previous two types of interregional spillovers so their individual roles can be evaluated.

Spatial Heterogeneity

In order to promote economic activity in a region, place-based economic policies are widely used across US states (Isserman 1993). Many states provide incentives such as R&D tax credits to encourage local firms to innovate (Moretti and Wilson 2014). Based on panel data over 1981-2004, Wilson (2009) finds that state R&D incentives significantly increase in-state R&D expenditures. Several empirical studies (Hauptman and Roberts 1987; Jaffe and Palmer 1997; Pickman 1998) indicate also that environmental and social regulations influence R&D investments and innovation.[5] Considering that each US state has different levels of incentives and regulations related to R&D, overlooking this institutional heterogeneity across states would lead to biased estimation results. As a result, we control for state-specific heterogeneity by using state dummy variables (***State***).

In addition, we assess the differences between metropolitan and non-metropolitan counties. Metropolitan areas are key places for knowledge production and spillovers (Feldman and Audretsch 1999; Fischer et al. 2001). Yet, we decide not to disregard non-metropolitan counties as their level of patenting and R&D expenses is not negligible and we want to avoid a sample selection bias. We control for this type of spatial heterogeneity with a dummy variable for the metropolitan counties (***MSA***) that interacts with the aforementioned knowledge input variables, with the exception of the control variable (***Size***) and the state dummies. Out of 3,109 counties, 853 counties are defined as metropolitan counties according to the 2000 US Census.

[TABLE 1]

Table 1 presents several descriptive statistics of the knowledge production variables. The median of total patent in metropolitan counties is 24 times greater than that of non-metropolitan counties. We also find important differences in the levels of private and academic R&D, more so across metropolitan counties. The column entitled "# of zero" reports the total number of counties with a value of zero for each variable. It turns out that more than 90% of non-MSA counties do not have any R&D expenditures over 1995-2002 although most of them created patents over 2003-2005. These statistics confirm our expectations regarding the larger share of innovation activities that takes place in the metropolitan counties. In order to examine the degree of geographical concentration, we calculate a Moran's I statistic (Cliff and Ord 1981) for each variable. The weight matrix for the statistic is constructed as in Equation (3) but implements a cut-off of 91 miles to ensure that each county has at least one neighbor. The results show that all our variables are significantly and positively clustered over space. We also note that the level of intra-county citations and the academic R&D expenses are less concentrated than the rest of the variables. The table also reveals that interregional knowledge spillovers, whether they are based on geographical proximity or on citation flows, are much greater across MSA than non-MSA counties. A similar difference is found when focusing on the level of intra-county spillovers. The extent to which each type of spillover contributes to the production of knowledge is measured in the next section.

Results

Using the aforementioned variables, we estimate restricted and unrestricted (MSA vs. non-MSA heterogeneity) regional knowledge production functions. Since most variables have a minimum value of zero, we added one to all variables before using a log transformation. The OLS estimation results appear in Table 2. Models 1 and 2 are estimated without spatial heterogeneity whereas Models 3 and 4 include it. All the models display significant heteroskedasticity (Breusch and Pagan 1979). In addition, the Moran's I statistics (Cliff and Ord 1981) indicates the significant presence of spatial autocorrelation in the OLS residuals (inference is based on 499 random permutations). As a result, we control for both heteroskedasticity and spatial autocorrelation in the error terms by applying the nonparametric spatial HAC (SHAC) estimator to the calculation of the variance-covariance (VC) matrix of OLS estimator (Kelejian and Prucha 2007, 138-144). Equation (5) presents the formula of the SHAC estimator. In the equation, $\hat{\Sigma}$ indicates the asymptotic SHAC VC matrix of OLS estimator. X_{ir} represents the (i^{th}, r^{th}) element of the explanatory matrix X and $\hat{\varepsilon}_i$ is the i^{th} OLS residual. d_{ij} measures the great circle distance between counties i and j in miles. The results reported here are based on the Parzen kernel function with a bandwidth of 91 miles.[6]

$\hat{\Sigma} = n(X'X)^{-1}\hat{\Psi}(X'X)^{-1}$ *and the* (r^{th}, s^{th}) *element of* $\hat{\Psi}$ *is such that* $\hat{\psi}_{rs} =$

$$\frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{n} X_{ir}X_{js}\hat{\varepsilon}_i\hat{\varepsilon}_j K\left(\frac{d_{ij}}{d^*}\right) \text{ where } K(\cdot) \text{ is a kernel function with a bandwidth } d^* \quad (5)$$

[TABLE 2]

Model 1 shows the estimation results using a 50 miles distance cut-off and assuming spatial homogeneity. Private and academic knowledge stocks have a positive influence on knowledge creation, although the former displays an elasticity that is nearly 2.4 times greater than the latter. The return on human capital is the largest among all variables. Sectoral diversity does not have a significant impact, which demonstrates that it is still difficult to conclude on the relative importance of diversity vs. specialization in the creation of knowledge. We find that a greater presence of large firms reduces knowledge creation. These results correspond to the argument of Acs et al. (1994) that small firms are more efficient at innovating than large ones. When it comes to knowledge spillovers, the intra-county citation flows display a positive and significant impact. The significance of localized interregional knowledge spillovers depends on their type. Private knowledge stock displays significant spillovers of which elasticity is around 58% of the elasticity of a county's own private knowledge stock. However, local academic spillovers do not have a significant role on knowledge production. The opposite result holds true for the distant interregional knowledge spillovers: only the academic spillovers have a significant role. A calculation of the overall return of private knowledge stock (own-region effect + interregional knowledge spillovers) indicates that it is 1.7 times greater than the overall effect of the academic knowledge stock. This result is smaller than the 2.2 ratio found in Anselin et al.

(1997, 436) although the comparison is not straightforward as the authors do not control for distant knowledge spillovers.

All the above results are fairly consistent when we extend the distance cut-off of local knowledge spillovers to 75 miles (Model 2). As a result, we move on to Model 3 that relies on the same cut-off as Model 1 but includes spatial heterogeneity in the form of MSA vs. non-MSA counties as suggested by a significant Chow-test.[7] We choose to use the non-MSA counties as the reference group so that the estimates for the MSA counties represent the difference with the reference group. Generally, the estimated returns display the same sign and significance level as their counterparts in Model 1 but their relative magnitude differs by county type. For example, in the non-MSA counties, private and academic knowledge stocks still influence knowledge creation positively and the former still has a greater elasticity than the latter (1.6 times greater whereas it was 2.4 in Model 1 where heterogeneity was not accounted for). Their returns do not show any statistical difference in the MSA counties; human capital still displays the greatest elasticity level and its return is 0.34 percentage points more productive in the MSA counties. Considering that the share of graduate degree holders is greater in MSA counties, these results confirm our expectations that the higher average level of human capital, the more rapid the growth of knowledge will be (Rauch 1993). We find that the presence of large firms still affects knowledge creation negatively. This result holds true both at the non-MSA and MSA level. Anselin et al. (1997) reach the same conclusion when working on the sample of MSAs.

One result that has changed compared to Model 1 is the role of sectoral diversity. It has a negative impact on knowledge creation at the 5% significance level. Hence specialization is beneficial in non-metropolitan areas whereas its impact in MSA counties (-0.164+0.193=0.029) is not statistically different from zero (p-value=0.76, two-side test). As such it is impossible to conclude whether sectoral specialization or diversity is more critical in metropolitan regions. When it comes to knowledge spillovers, the role of intra-regional spillovers as well as university interregional spillovers is spatially homogenous. Conversely, the interregional spillovers of private knowledge have a statistically different effect in the MSA counties. Indeed, both localized and distant spillovers of private knowledge stock have a greater effect in MSA counties. They are respectively 0.025 and 0.081 percentage points above what is expected in non-MSA counties.

We believe that the differences in the returns of interregional spillovers generated in the academia vs. the private sector are due to by their respective learning cost and the absorptive capacity of recipient regions. External knowledge is more easily absorbed in recipient regions that have a larger stock of knowledge (Verspagen and Schoenmakers 2004), which provides a significant advantage to MSA counties over their non-MSA counterparts. In addition, Cohen and Levinthal (1990) point out that a recipient's willingness to bear the cost associated to learning new knowledge is another important determinant of the absorptive capacity. Since universities share their knowledge with others at relatively low cost (Liu 2013), even for free in some cases, external innovators are able to access it relatively easily and without the need for a large absorptive capacity. On the other hand, private companies bear greater R&D costs, hence they are more reluctant to share new knowledge or they try to stay their sole proprietor for as long as possible. Therefore, recipient regions require a much greater absorptive capacity and/or need to afford higher cost to comprehend private knowledge. These elements explain the differences between the knowledge spillovers generated in the academia (their returns are spatially homogenous) and those due to the private sector (their returns are larger in MSA counties because they have a greater absorptive capacity than non-metropolitan counties).

For both Models 1 and 3, our results do not conclude to a significant presence of localized interregional spillovers of academic knowledge. It is a different outcome from many previous studies applied to the US (Jaffe 1989; Acs et al. 1994; Audretsch and Feldman 1996; Anselin et al. 1997; Ó hUallacháin and Leslie 2007). Re-estimating our models without long-distance spillovers does not change this result, so the explanation is not found in previous papers displaying a missing variable bias. Instead, we believe that one possible explanation lies in our use of sectorally aggregated data. According to Anselin et al. (2000), the influence of local university spillovers vary by industry. They find that local university spillovers are found in the Electrics and the Instruments sectors but not in the Drugs/Chemicals nor Machinery sectors. Since aggregating sectoral innovation data attenuate heterogeneous characteristics of local spillovers across sectors, our results may not show strong evidence of localized academic spillovers.

Another possible explanation is the spatial scale of our data. The spatial observations used in previous studies are the states (Jaffe 1989; Audretsch and Feldman 1996; Anselin et al. 1997) and the MSAs (Anselin et al. 2000; Acs et al. 2002) which have a broader spatial extent than our county-level data. It is possible that the 50 miles distance cut-off is somewhat too narrow to capture the interregional spillovers of academic knowledge at the county-level as suggested by the sparseness of the geographical distribution of academic knowledge: 43% of the non-MSA counties and 16% of the MSA counties do not have a neighbor spending in academic R&D within 50 miles. When the cut-off increases to 75 miles, the shares reduce to 22% and 6% respectively. As such, we test the sensitivity of the interregional spillovers with a 75 miles distance cut-off and the results are reported in Model 4. The results are very consistent with those of Model 3; the only exception is the presence of positively significant localized spillovers from academic knowledge although they are only weakly significant (at 10%). Their role is not different between MSA and non-MSA counties.

[TABLE 3]

We decided to estimate two additional model specifications to test the robustness of our results. The first one is a spatial Durbin error model (SDEM) and the second one is a Tobit model coupled with spatial error model (Tobit SEM)[8]. The latter one allows us to explicitly control for the 438 counties that do not produce any patent. The SDEM is estimated by the generalized method of moments (GMM) estimator suggested by Kelejian and Prucha (2010) to control for heteroskedasticity. Models 5 and 6 in Table 3 show the estimation results of the SDEM with 50 and 75 miles distance cut-offs respectively. The spatial weight matrix of the SDEM is the W matrix with a 91 mile cut-off used when calculating the Moran's I statistics in the OLS residuals. Significant spatial error autocorrelation is found for both distance cut-offs. All estimates and the model fit (adjusted R^2, AIC, BIC) of the SDEM are very close to those of the OLS model.

Before we estimate the Tobit SEM, we check the minimum value of the positive patents (0.0303) so that its log value (-3.496608) is used as the left limit to censor the zero patents. A robust maximum likelihood estimator (Greene 2011, 542-545) is used for its estimation. Models 7 and 8 in Table 3 report the results for different distance cut-offs. Although the negative impact of sectoral diversity and the returns of human capital and localized spillovers of private R&D across MSA counties are not statistically significant, the results are qualitatively similar to OLS. In terms of model fit, OLS outperforms the Tobit SEM. As a result, the estimates of the SDEM and Tobit SEM do not challenge the findings based on OLS coupled with SHAC estimator. In addition, the latter has the conceptual advantage over the other two of not being sensitive to the structure of the spatial weight matrix because SHAC does not make any assumption about the structure of the disturbances (Piras 2010).

Conclusion

Identification and measurement of knowledge spillovers have attracted a lot of attention in the knowledge production function literature over the last few decades. The majority of studies have modeled localized interregional knowledge spillovers based on pure geographical proximity as if face-to-face contacts are their only source. Although such contacts favor spillovers of tacit knowledge that should not be disregarded, we demonstrate in this paper that distant sources of knowledge can contribute even more to the creation of local knowledge. In order to capture these types of externalities, we build a matrix of the patent creation-citation flows across the 3,109 US counties that constitute our sample. Its advantage compared to geography-based matrices relies on its capacity to provide clearly the directionality of the knowledge flows. In addition, this paper examines explicitly the role of intra-regional knowledge spillovers as it has been largely ignored in past studies.

Our estimation results indicate that all types of spillovers (intra-regional spillovers, localized and distant interregional spillovers) play a significant role in the production of knowledge, although their relative impact depends on their type, source, and location. Intra-regional spillovers and distant interregional spillovers display greater returns than those based on localized spillovers. This implies that previous contributions that emphasized the latter type of knowledge spillovers were unable to fully capture their role in innovation. We find that localized spillovers of private investment in R&D lead to greater returns than those due to university R&D. In addition, localized spillovers generated in the private sector display greater returns in MSA than non-MSA counties. Distant knowledge spillovers due to university R&D have a significant and spatially homogenous return across MSA and non-MSA counties, while those attributed to private R&D contribute to innovation in MSA regions only. Generally, the MSA counties are able to benefit more from the research performed elsewhere than their non-MSA counterparts.

Our results lead to two policy implications. First, future innovation policies should recognize more fully the presence of spatial heterogeneity in the innovation process. Some contributions have highlighted the need to “regionalize” such policies (Stough 2003; Fritsch and Stephan 2005). Indeed, our estimation results show that if policy makers ignore the significant heterogeneity between metropolitan and non-metropolitan regions, the overall return of private investments in R&D will be over-estimated, especially in the non-MSA counties. This could encourage policy makers to systematically allocate their resources in support of R&D in the private sector instead of in the academia. Yet, our results show that the overall returns of private and university R&D are similar in non-MSA counties. In addition, it is only when spatial heterogeneity is included in our model that the significant role of distant knowledge spillovers of private knowledge can be revealed (in MSA counties only). Some metropolitan regions have become a hub of global knowledge (Maskell et al. 2006), hence the lack of consideration for distant knowledge spillovers can overemphasize the importance of localized private R&D interactions and lead to suboptimal innovation policies.

Second, the role of universities as an engine of both regional and national innovation is confirmed in our results and supports previous contributions (Jaffe 1989; Anselin et al. 2000; Ponds et al. 2010). While the returns in R&D in the academia are not as high as in the private sector, more especially among MSA counties, they have the advantage to display significantly positive long-distance spillovers that, in addition, maintain their influence in the innovation process across types of counties. In comparison, private R&D spending in non-MSA does not lead to any long-distance spillovers. As a result, innovation policy measures need to consider the larger geographical extent of academic knowledge spillovers when evaluating the relative performance of the actors of innovation and providing financial support such as grants and tax breaks.

In this paper we examined the role of local and distant knowledge spillovers based on geographical proximity and patent creation-citation flows respectively. Although our empirical results have highlighted the importance of these types of spillovers, we are aware that other channels such as those based on labor migration (Almeida and Kogut 1999) are worth exploring further. They too would indicate the directionality of spillovers. To our knowledge, the role of these factors has never been measured in the frame of a US county-level knowledge production function, yet they could shed light into the dynamics of the interregional system of innovation. We leave this endeavor for future research.

[1] We test the sensitivity of our estimation results to a 12% and 15% depreciation rate. We conclude that our estimation results are generally consistent across rates.

[2] The US Small Business Administration uses this standard to define a small business. Previous studies adopt the same standard to define a small firm (Acs and Audretsch 1988; Anselin et al. 1997).

[3] Our distance cut-offs are based on previous studies measured across US metropolitan areas such as Anselin et al. (1997), Acs et al. (2002) and Mukherji and Silberman (2013). The cut-off distances are based on the commuting patterns (e.g. Smallen 2004; Rapino and Fields 2013) and are chosen to capture the knowledge spillovers that take place via face-to-face interactions. While 75 miles may seem a long distance, the US Department of Transportation (Smallen 2004) reports that as many as 3.3 million Americans are "stretch commuters" traveling more than 50 miles one-way to work. Stretch commuters living in rural areas drive up to 99 miles daily (Smallen 2004).

[4] According to Fischer and Wang (2011, 50-51), an inverse distance decay function is not an interaction form that is generally observed. As such, we prefer an inverse exponential decay function that is widely used in the literature (e.g. Bode 2004; Fischer et al. 2006). We define various distance decay parameters (0.01, 0.05, 0.1, 0.15, 0.17, 0.2, 0.23, and 0.25) and measure the model performance in terms of adjusted R^2, the Akaike Information Criterion, and the Bayesian Information Criterion. The best model fit is obtained with a distance decay parameter of 0.17. All results are available upon request.

[5] For example, Jaffe and Palmer (1997) find a significant relationship between R&D expenditures and compliance costs associated to environmental regulations. See Stewart (2012) for a more comprehensive literature review about regulations, innovation, and R&D investment.

[6] We use the function "spreg" of the R package "sphet" (Piras 2010) to implement the SHAC estimator. While it offers several kernel functions, we choose the Parzen kernel because it has the steepest decay and is thus the closest function to the inverse exponential function with a distance decay parameter of 0.17. However, we have tried all the other kernels and the standard errors of the results are not very sensitive to them. All the results are available from the authors upon request.

[7] The Chow F-test (Chow 1960) rejects the null hypothesis of structural homogeneity between MSA and non-MSA counties for both the 50 and 75 miles distance cut-offs at the 1% significance level. F statistics are 38.15 (d.f. 1=12, d.f. 2=3,085) and 39.16 (d.f. 1=12, d.f. 2=3,085) for 50 and 75 miles respectively.

[8] We thank an anonymous reviewer for suggesting these model specifications. The SDEM with robust standard errors is estimated with the function "gstslshet" of R package "sphet" developed by Piras (2010). The Tobit SEM is estimated with Stata's module "SPAUTOREG" developed by Shehata (2012).

TABLE 1. Descriptive Statistics

		Total (3,109)	Non-MSA county (2,256)				MSA county (853)			
Variable	Explanation	Moran's I	Mean	Median	S.D.	# of zero	Mean	Median	S.D.	# of zero
Patent	Total patents (fractional count)	0.74	3.4	0.9	9.2	433	150.9	22.4	494.3	5
Private	Private R&D ($1,000)	0.75	2,562.6	0.0	51,096.1	2,100	821,238.4	10.0	4,909,446.0	423
Univ	Academic R&D ($1,000)	0.26	3,844.6	0.0	52,053.5	2,154	139,803.4	0.0	587,920.1	569
Graduate	Share of graduate degree (%)	1.03	3.1	2.7	1.4	0	5.1	4.4	2.8	0
Diversity	Level of sectoral employment diversity	0.49	2.8	2.7	0.9	0	4.5	4.4	1.5	0
Large	Share of large firms (%)	0.37	7.7	7.6	3.4	35	8.4	8.0	3.1	0
Intra	Share of intra citation (%)	0.21	5.3	0.0	14.5	1,731	11.9	10.5	11.7	164
W50*Private	Spatial lag of private R&D within 50 miles	1.46	1,197.3	0.7	7,203.5	1,010	156,065.0	2,611.5	868,314.2	115
W50*Univ	Spatial lag of academic R&D within 50 miles	1.20	1,199.1	3.2	5,718.0	981	22,842.2	1,042.7	98,245.8	137
W75*Private	Spatial lag of private R&D within 75 miles	1.46	1,246.4	6.2	7,241.3	498	156,361.4	2,853.2	868,534.2	49
W75*Univ	Spatial lag of academic R&D within 75 miles	1.23	1,215.2	17.4	5,719.9	482	22,885.6	1,118.2	98,246.2	49
M50*Private	Spatial lag of private R&D over 50 miles	0.43	13,420.2	834.9	38,261.2	911	554,273.5	95,399.4	1,694,144.0	27
M50*Univ	Spatial lag of academic R&D over 50 miles	0.46	3,241.2	57.6	9,630.0	987	108,505.4	22,761.0	318,639.9	35
M75*Private	Spatial lag of private R&D over 75 miles	0.43	13,124.7	816.4	37,021.9	915	541,172.4	92,510.5	1,671,672.0	27
M75*Univ	Spatial lag of academic R&D over 75 miles	0.46	3,179.5	52.9	9,531.9	989	106,991.6	22,649.5	317,264.5	35
Size	Total employees	0.59	10,384.5	7,265.0	10,025.0	1	123,651.5	58,219.0	230,296.7	0

Note: Moran's I statistics are calculated by using the spatial weight matrix of the inverse exponential decaying function with the distance decay parameter of 0.17 within 91 miles to ensure having at least one neighbor region. The p-values of the statistics are all significant at 1% and they are calculated by using the permutation method of 499 random draws. The column of # of zero means the number of counties of having zero values for each variable.

TABLE 2. Estimation Results of OLS

	Model 1 (OLS) Distance cut-off: 50 miles Estimate	(SHAC S.E.)		Model 2 (OLS) Distance cut-off: 75 miles Estimate	(SHAC S.E.)		Model 3 (OLS) Distance cut-off: 50 miles Estimate	(SHAC S.E.)		Model 4 (OLS) Distance cut-off: 75 miles Estimate	(SHAC S.E.)	
Intercept	-4.209	(0.208)	***	-4.214	(0.209)	***	-3.494	(0.200)	***	-3.486	(0.200)	***
ln Private	0.076	(0.005)	***	0.077	(0.005)	***	0.043	(0.008)	***	0.043	(0.008)	***
ln Univ	0.032	(0.004)	***	0.031	(0.004)	***	0.027	(0.008)	***	0.027	(0.008)	***
ln Graduate	0.755	(0.046)	***	0.760	(0.046)	***	0.582	(0.053)	***	0.586	(0.053)	***
ln Diversity	-0.060	(0.062)		-0.062	(0.063)		-0.164	(0.072)	**	-0.177	(0.072)	**
ln Large	-0.237	(0.031)	***	-0.235	(0.032)	***	-0.165	(0.028)	***	-0.164	(0.028)	***
ln Intra	0.093	(0.011)	***	0.094	(0.011)	***	0.083	(0.012)	***	0.084	(0.012)	***
ln W*Private	0.044	(0.005)	***	0.047	(0.006)	***	0.027	(0.005)	***	0.026	(0.006)	***
ln W*Univ	0.006	(0.004)		0.006	(0.005)		0.007	(0.005)		0.010	(0.005)	*
ln M*Private	0.001	(0.006)		0.002	(0.005)		0.003	(0.005)		0.005	(0.005)	
ln M*Univ	0.039	(0.006)	***	0.038	(0.006)	***	0.031	(0.006)	***	0.029	(0.006)	***
MSA							-1.419	(0.321)	***	-1.493	(0.320)	***
MSA*ln Private							0.012	(0.009)		0.011	(0.009)	
MSA*ln Univ							-0.011	(0.009)		-0.010	(0.009)	
MSA*ln Graduate							0.339	(0.092)	***	0.334	(0.092)	***
MSA*ln Diversity							0.193	(0.107)	*	0.218	(0.107)	**
MSA*ln Large							-0.076	(0.093)		-0.061	(0.093)	
MSA*ln Intra							0.018	(0.023)		0.017	(0.023)	
MSA*ln W*Private							0.025	(0.008)	***	0.035	(0.009)	***
MSA*ln W*Univ							-0.008	(0.009)		-0.015	(0.010)	
MSA*ln M*Private							0.081	(0.021)	***	0.077	(0.020)	***
MSA*ln M*Univ							0.024	(0.020)		0.029	(0.020)	
ln Size	0.503	(0.026)	***	0.501	(0.026)	***	0.451	(0.025)	***	0.450	(0.025)	***
State dummies	Yes			Yes			Yes			Yes		
Total Observations	3109			3109			3109			3109		
BP test	230.076	***		229.670	***		207.971	***		205.568	***	
Moran's I	0.114	***		0.116	***		0.130	***		0.130	***	
Adjusted R^2	0.882			0.882			0.897			0.897		
AIC	-1.133			-1.128			-1.260			-1.260		
BIC	-1.016			-1.012			-1.122			-1.122		

Note: * P-value< 10%, ** P-value< 5%, *** P-value< 1%. W means the spatial weight matrix based on the inverse exponential decaying function with the distance decay parameter of 0.17 within 50 or 75 miles. M stands for the spatial weight matrix based on the patent citation flows over 50 or 75 miles. Moran's I statistics are calculated by using the W matrix but within 91 miles to ensure having at least one neighbor region. Standard errors are spatial HAC standard errors (Kelejian and Prucha 2007) using the Parzen kernel function with the bandwidth of 91 miles.

TABLE 3. Estimation Results of SDEM and Tobit SEM

	Model 5 (SDEM-GMM) Distance cut-off: 50 miles			Model 6 (SDEM-GMM) Distance cut-off: 75 miles			Model 7 (Tobit SEM-ML) Distance cut-off: 50 miles			Model 8 (Tobit SEM-ML) Distance cut-off: 75 miles		
	Estimate	(Robust S.E.)		Estimate	(Robust S.E.)		Marginal Effects	(Robust S.E)		Marginal Effects	(Robust S.E)	
Intercept	-3.492	(0.190)	***	-3.486	(0.191)	***	-7.721†	(0.328)†	***	-7.715†	(0.328)†	***
ln Private	0.042	(0.008)	***	0.043	(0.008)	***	0.033	(0.010)	***	0.033	(0.010)	***
ln Univ	0.027	(0.007)	***	0.027	(0.007)	***	0.021	(0.010)	**	0.020	(0.010)	**
ln Graduate	0.573	(0.052)	***	0.578	(0.052)	***	0.934	(0.092)	***	0.945	(0.092)	***
ln Diversity	-0.151	(0.068)	**	-0.163	(0.068)	**	-0.017	(0.115)		-0.039	(0.115)	
ln Large	-0.166	(0.028)	***	-0.165	(0.028)	***	-0.184	(0.062)	***	-0.180	(0.062)	***
ln Intra	0.083	(0.011)	***	0.084	(0.012)	***	0.114	(0.018)	***	0.116	(0.017)	***
ln W*Private	0.028	(0.005)	***	0.028	(0.006)	***	0.044	(0.009)	***	0.045	(0.010)	***
ln W*Univ	0.006	(0.005)		0.008	(0.005)		0.010	(0.008)		0.014	(0.010)	
ln M*Private	0.003	(0.005)		0.005	(0.005)		0.012	(0.010)		0.015	(0.010)	
ln M*Univ	0.031	(0.006)	***	0.028	(0.006)	***	0.042	(0.011)	***	0.037	(0.011)	***
MSA	-1.420	(0.278)	***	-1.496	(0.278)	***	-1.040	(0.377)	***	-1.116	(0.376)	***
MSA*ln Private	0.013	(0.009)		0.012	(0.009)		-0.002	(0.011)		-0.003	(0.011)	
MSA*ln Univ	-0.010	(0.009)		-0.009	(0.009)		-0.018	(0.010)	*	-0.017	(0.010)	
MSA*ln Graduate	0.388	(0.085)	***	0.381	(0.086)	***	0.158	(0.115)		0.147	(0.115)	
MSA*ln Diversity	0.130	(0.098)		0.155	(0.098)		-0.070	(0.135)		-0.035	(0.135)	
MSA*ln Large	-0.066	(0.077)		-0.052	(0.076)		0.154	(0.103)		0.168	(0.102)	
MSA*ln Intra	0.016	(0.022)		0.015	(0.022)		-0.014	(0.028)		-0.016	(0.028)	
MSA*ln W*Private	0.025	(0.009)	***	0.035	(0.010)	***	0.011	(0.011)		0.019	(0.013)	
MSA*ln W*Univ	-0.004	(0.009)		-0.011	(0.010)		-0.003	(0.011)		-0.010	(0.013)	
MSA*ln M*Private	0.079	(0.020)	***	0.075	(0.019)	***	0.081	(0.026)	***	0.077	(0.026)	***
MSA*ln M*Univ	0.024	(0.020)		0.029	(0.020)		0.005	(0.027)		0.010	(0.027)	
ln Size	0.451	(0.023)	***	0.450	(0.023)	***	0.738	(0.032)	***	0.735	(0.032)	***
Lambda	0.420	(0.091)	***	0.421	(0.091)	***	0.037†	(0.017)†	**	0.038†	(0.017)†	**
Sigma							0.802†	(0.015)†	***	0.802†	(0.015)†	***
State dummies	Yes			Yes			Yes			Yes		
Total Observations	3109			3109			3109 (Left-Censored Obs.: 438)			3109 (Left-Censored Obs.: 438)		
Moran's I	0.177	***		0.179	***							
Adjusted R^2	0.896			0.896			0.803			0.803		
AIC	-1.257			-1.258			0.281			0.280		
BIC	-1.117			-1.118			0.419			0.418		

Note: * P-value< 10%, ** P-value< 5%, *** P-value< 1%. Superscript † indicates robust ML estimates in Models 7 and 8. Other estimates in Models 7 and 8 present marginal effects of explanatory variables on observed ln Patent, i.e. $\beta \cdot$ Prob(-3.496608 < ln Patent) and its standard errors are calculated by the delta method. W means the spatial weight matrix based on the inverse exponential decaying function with the distance decay parameter of 0.17 within 50 or 75 miles. M stands for the spatial weight matrix based on the patent citation flows over 50 or 75 miles. Spatial error terms of SDEM and Tobit SEM are based on the W matrix within 91 miles. Moran's I statistics are calculated by using the W matrix but within 91 miles to ensure having at least one neighbor region. The adjusted R^2 of Tobit SEM is calculated following Buse (1973).

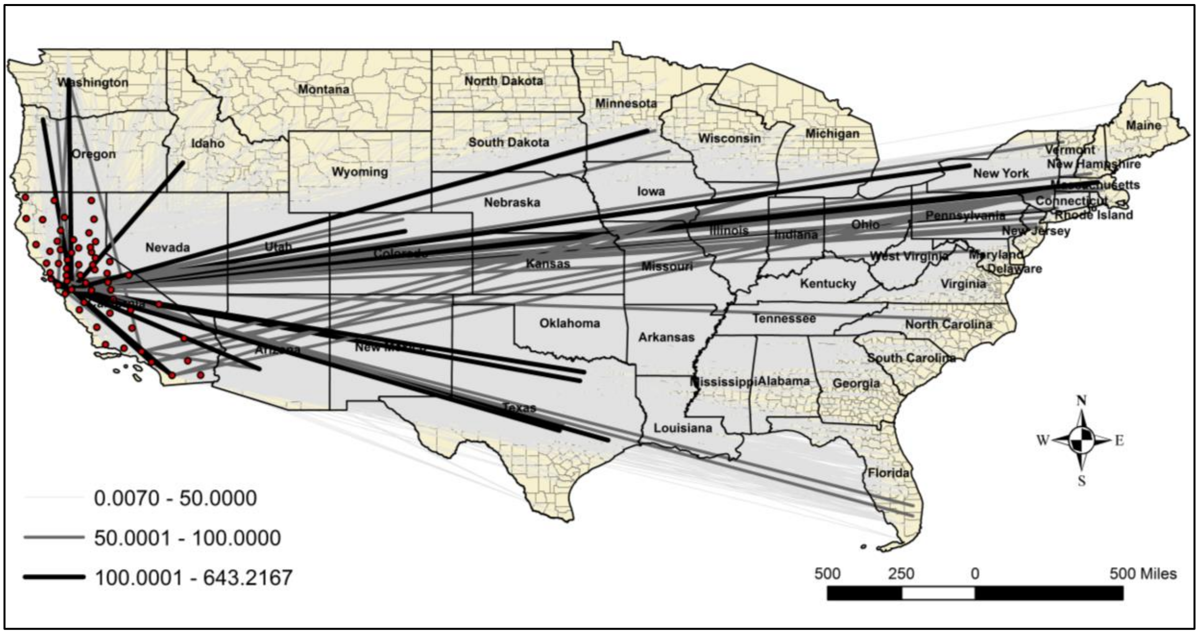

FIGURE 1. California's Patent Citing Pattern (using the fractional counting method)

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