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21 July 2014

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Abstract

This paper studies the diffusion of knowledge and its consequences for local innovation production. In a common framework, we analyze the geographic reach of different channels of knowledge flows that thus far have been studied separately in the literature. To jointly estimate these flows, we develop and apply novel econometric techniques appropriate to the nature of the data. We find that geographic along with technological proximity to be more essential to the operation of market than to non-market channels of knowledge flows. External accessible disembodied knowledge has a strong positive effect on local innovation production as large as that of homegrown knowledge.

Keywords: knowledge flows, patents, citations, inventor mobility, trade, non-linear regression systems
JEL: C11, C33, O30, O51

1. Introduction

Economic growth is driven by innovation activity carried out locally as well as by the ability of a region to learn from external technological achievements (Romer, 1986; Grossman and Helpman, 1991).

The contribution of knowledge flows on the shape of the geographical distribution of innovative and economic activities and consequently on inequality among regions and countries (Saxenian, 1994; Swann et al., 1998; Verspagen, 1999), has motivated scholars to document them and study their boundaries. A voluminous literature has progressed on separate avenues, however, depending on how knowledge flows are inferred.

Most notably, the patent-citation literature, initiated by the seminal work of Jaffe et al. (1993) and followed by numerous subsequent studies (Branstetter, 2001; Peri, 2005; Mancusi, 2008), traces-out technological learning via citations of patents.[1] The principal assumption there is that a citation from a patent to

☆We are grateful to Stuart Graham, Alan Marco, Kirsten Apple, Saurabh Vishnubhakat, Galen Hancock and staff of the Office of the Chief Economist at the United States Patent and Trademark Office (USPTO) for their wise assistance and generous support. We thank Adamandia Karaiskaki and Cathrin Linardaki for excellent research assistance. We also thank Juan Alcacer, Bertrand Candelon, George Deltas, Elias Dinopoulos, Rachel Griffith, Zen Lei, Giovanni Peri, Carlos Serrano, Bart Verspagen, Brian Wright, Arvids Ziedonis and seminar and conference participants at Adams Business School, University of Glasgow (Glasgow, 2014), at the Conference on the Economics of Innovation and Patenting (ZEW/MaCCI, 2013), at the Conference on Research on Economic Theory & Econometrics (Naxos, 2013), and at the European Policy for Intellectual Property Conference (Paris, 2013) for useful insights. Kyriakos Drivas gratefully acknowledges financial support from the National Strategic Reference Framework No: SH1_4083. The usual disclaimer applies.

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[1]A parallel literature infers knowledge flows via citations of research papers (Belenzon and Schankerman, 2013). The later channel, however, captures knowledge diffusion mostly within academia. Furthermore, citation of papers reflect scientific rather than commercial aspects of technological knowledge.

another indicates that inventors of the latter patent knew and used the former.[2]

Knowledge flows can be also mediated by market mechanisms. A rich research avenue, the trade-growth literature, infers technological learning by analyzing trade flows (Coe and Helpman, 1995; Keller, 2002). According to this literature, importing a foreign intermediate good allows a recipient country to learn from the R&D-, or 'technology'-content embodied in the traded good. Consequently, merchandise trade acts as an important conduit of market-based knowledge flows across regions. The trade-growth literature, however, has been reluctant to incorporate information on patent citations and technological space of the interaction units.

Another strand of research studies trade of patented ideas, instead, as a vehicle of market-generated knowledge flows (Spulber, 2008). Technology transfer from a firm to another can take place via the market of intellectual property.[3] Businesses, for example, buy patents to use the technology covered by the patent, which could be vital for their production and the buyer's willingness-to-pay depends on the technological knowledge contained in the patent (Anton and Yao, 1994). Further, the buyer of a patent can develop connections with the seller in order to acquire the "how-to" knowledge to implement the patented technology.[4] Research in this field, has documented evidence on national and international transfers of intellectual property rights and spread of technological knowledge in a number of countries using historical data (Nicholas, 2010; Moser, 2011; Burhop and Wolf, 2013). A recent stream of research by Serrano (2010, 2011) develops models of costly technology transfer and renewal in the market for innovation to quantify possible gains from trading patents as well as costs of adopting technology in the market for patents, while a strand of research infers knowledge flows by studying the flows of academic licensed patents using proprietary data of a (small) number of US universities (Mowery and Ziedonis, 2001).

Finally, a separate branch of literature documents evidence on learning via the mobility of highly skilled personnel. The focus on job moves of patent inventors is based on the assumption that ideas and knowledge are embodied in the minds of individuals (Feldman, 2000) and, consequently, job movements enable an inventor to take advantage of knowledge - not only codified, but also tacit - accumulated by other inventors in inventor's past jobs and share it in later jobs. A number of studies, in this literature, have extensively investigated the migration of inventors as a potential channel of market-generated knowledge diffusion. For example, Kim and Marschke (2005) explore the linkages between inventors' mobility and knowledge flows in the nanotechnology sector confirming that the mobility of inventors enhances the citations across patents of firms that the inventor was previously employed. Similar conclusions are also drawn by Agrawal et al. (2006), who document knowledge flows to an inventor's prior location are approximately 50% greater than if the inventor had never lived there, suggesting that social relationships, not just physical proximity, are important for determining flow patterns.[5] Rather than studying citations exchanged between inventors, Giuri and Mariani (2013) focus on the interactions between inventors that were important for the development of a patent using survey data for european patent inventors.

This paper aims to jointly study the relative mobility of most notable channels of knowledge flows, which thus far have been studied by separate literature avenues, in one common framework and assess their individual consequences for local innovation production in the US. In doing so, we use newly con-

[2]The awareness of the citing patent inventor about the cited patent (i.e., the amount of information about the content of the cited patent actually reached the possible unaware citing inventor) has raised criticisms about how much actual knowledge patent citation flows indeed capture (Alcacer and Gittelman, 2006; Harhoff et al., 2008). A crucial factor is that citations in patents are the results of a highly mediated process, which involves the patent inventor, the patent attorney and the patent examiner. Despite the limitations, studies (Jaffe et al., 2000) have shown that patent citations can be used as a proxy of knowledge flows as about 40% of the inventors surveyed indicated that they learned about the cited invention either before or during the development of their invention.

[3]In addition to increasing the rate of innovation - the inventor can just sell the patent to a specialized producer and focus his own efforts on the next invention - patent transactions improve the allocation of technology in an economy. As knowledge production is highly concentrated in space (Audretsch and Stephan, 1996), the market of patents facilitates the stretch of patented ideas in space as potential buyers can purchase innovations without having to re-invent them.

[4]A concern, however, in using patent trades, as a potential channel of technological knowledge flows, is that companies could also buy patents for strategic, e.g., defensive - to help defend the patents the company already owns by acquiring similar technology - negotiating and blocking purposes. Disentailing, however, the reason of a patent transaction, whether its technology acquisition or pure strategy, is not easy as there is no available information.

[5]See Miguelez et al. (2010) for an excellent survey of the literature.

structed data, and develop and apply appropriate estimation techniques.

More specifically, in this paper, we jointly study the geographic diffusion of knowledge via four channels namely, patent citations, trade of goods, trade of patents, and inventors' mobility, in order to assess the importance of each channel in the diffusion of knowledge and on local innovation production. With our approach, we are able to contribute to important discussions in the literature, for instance, whether the generation mechanism of knowledge flows, i.e., market-based flows (traded patents, inventors' mobility, trade of goods) versus non-market spillovers (citations), matters for the geographic stretch of knowledge diffusion (Audretsch and Stephan, 1996). We are also able to quantify and compare the importance of disembodied knowledge that operate via trade of patents and citation exchange versus embodied knowledge in inventors and goods for local innovation production (Grossman and Helpman, 1991; Rivera-Batiz and Romer, 1991). The study of different channels of knowledge diffusion within a simple, common framework of analysis, compatible with different literature traditions, consists the first contribution of this paper.

So far, in comparing the geographic mobility of different types of knowledge flows one had to resort in borrowing estimates from different research branches of the literature. Cross-study comparisons, however, are not always easy due to different model specifications and level of analyses. Further, possible interdependencies across different channels and omitted factors (e.g. technology shocks) when estimating single equations of knowledge flows could hamper the efficiency of the estimates (Zellner, 1962).[6] To perform proper comparisons, one needs to jointly estimate knowledge flows that operate via different channels as a system. In doing so, two challenges emerge. First, the potential existence of (unobserved) heterogeneity and second, the different nature of the dependent variables as some flows are count data (traded patent flows, citation flows and inventor flows), whereas some others (trade of goods) are continuous. Existing econometric studies (Winkelmann, 2000) develop non-linear system estimation techniques only for count data, without accounting for unobserved heterogeneity in the data or for different types of responses such as count and continuous.

In this paper, we consider these challenges and develop multivariate system estimation techniques. We first extend the work of Winkelmann (2000) to account for potential unobserved heterogeneity in the data. Second, to account for the different nature of the data, we propose, for the first time in the literature, estimation techniques for systems of mixed count and continuous responses. We, therefore, estimate a system of gravity-like equations, where the dependent variables, citation flows, trade of goods, patent trade flows, and inventor flows, are explained by geographic and technological factors. The development and application of novel and appropriate econometric techniques consists the second contribution of this paper.

The study of different channels of knowledge flows across states of the US and the effect of each channel on a state's innovation production, constitutes our third and last contribution. The US is one of the most prolific nations as far as innovation activity is concerned. The geographic structure of the US, the contiguous states, the fairly high degree of institutional homogeneity, the common currency, the large number of states, make the US an excellent candidate to sharp our understanding on the mechanisms of knowledge diffusion and the acclaimed influence of border and distance in shaping knowledge flows.

Our paper relates to and complements a number of important works in the literature. For example, the seminal study of Jaffe et al. (1993) examines the role of geographic distance as the major resistance factor of citation flows in the US. Subsequent studies of Peri (2005), Thompson (2006), and Alcacer and Gittelman (2006) extend the work of Jaffe et al. (1993) in various aspects. Among these studies, we mostly relate to the work of Peri (2005), who examines the determinants of citation flows and their effect on innovate activity across world's regions. We are also conceptually close to the work of Mowery and Ziedonis (2001), which examines knowledge flows via two channels, the channel of market of intellectual property (patent licenses) and the channel of non-market spillovers (citations), showing that formal knowledge flows, operating by academic licensing, are more bounded by geographic distance compared to informal flows exemplified by patent citations. However, as the authors state, their sample is small, consisting of four US universities, and focuses only on academic patents.

[6]For instance, rapid technological change reflected in higher patent trade and citation exchange and expanding trade of goods could become a unified force affecting labor markets, including the market of inventors (Autor et al., 2013).

We apply our modeling approach to the states of the US over the period 1993-2006 with two key questions in mind: (i) How important is proximity for knowledge mobility? (ii) Does available knowledge contribute to local production of innovation?

The evidence we provide is straightforward: Proximity, even within the same country, matters for knowledge flows. Gravity emerges everywhere, in the embodied knowledge flows as well as in the world of ideas. We find, however, that disembodied knowledge, generated from patented ideas, which are traded and cited, is less geographically restricted and, therefore, its effective reach is beyond that of knowledge embodied in traded goods or inventor flows, as the latter involve movements of goods and people, respectively. Further, non-market knowledge flows are more far-reached than market-based flows, with inventor flows to be the most geographically confined among the market-based flows. As our estimates show, market-generated flows are much more information intensive than non-market flows and, therefore, proximity there plays a pronounced role. The very significant impact of border and distance especially on ideas exchange (traded patent and citation flows) across states of the US most probably reflects information frictions as state border and distance act as barriers to social interactions and connectedness of economic agents. In addition, technological proximity, in terms of technological effort of states and technological specialization similarities, appears to be also very important. Similarity of technological efforts (e.g. spending on R&D and number of scientists) benefits knowledge diffusion mostly via inventors' mobility, while production structure closeness matters most for knowledge flows via patent trade. Overall, results remain robust for different variable definitions, sub-samples, and alternative specifications.

The implications of our findings for the growth literature are potentially relevant. Although theoretical studies (Grossman and Helpman, 1991; Rivera-Batiz and Romer, 1991) emphasize the important consequences of disembodied knowledge flows over knowledge embodied in the trade of goods, there has been little effort, on the empirical side, to thoroughly explore this issue. Along with other important studies, this paper makes an effort toward analyzing knowledge diffusion via different channels and their effect on local innovation activity. We find that knowledge flows are relevant to a state's innovation production, as external accessible R&D gained through different flows has a strong positive effect on a state's innovation activity, which is as large as that of state's own R&D stock. Further, the effective reach of disembodied knowledge flows, exemplified via citation and traded patent flows, is larger than that of knowledge embodied in goods and inventors, confirming thus the importance of disembodied flows for technology transfer and economic growth.

The remainder of the paper proceeds as follows. Section 2 introduces the framework for analyzing knowledge flows and the estimation techniques. Section 3 discusses the data. Section 4 presents the results. Section 5 summarizes the findings and concludes.

2. A Framework of Analysis

2.1. Modeling Knowledge Flows

We begin by describing the production of innovation activity of a region (state, in our case). The innovation output of a region is determined by the homegrown technological knowledge of the region as well as by the external, but accessible (or 'borrowed') to the region technological knowledge of other regions (Griliches, 1992). In its simple form, the production function of innovation of a region can be expressed as follows:

$$Q_{it} = (A_{it})^{\gamma} (A^{\alpha}_{it})^{\mu} \tag{1}$$

where Q is the innovative output, proxied by the number of patents produced in state i; A is own, homegrown knowledge stock, proxied by R&D stock accumulated from past and current R&D investments in state i; and A^{α} is the stock of external and accessible (hence the α superscript) to state i knowledge stock, proxied by R&D accumulated in states other than i at time t.

Knowledge flows take place when an idea, generated in region, country or institution, is learned by another region, country or institution. If knowledge flows manage to perfectly and completely spill over, then the amount of external knowledge that eventually reaches state i is simply the summation of all borrowed knowledge that comes from all other states. In reality, however, the diffusion of knowledge flows across states may be less than complete; only a share of research results from other states reaches state i. Therefore, the external accessible to state i R&D activity can be described by:

$$A_{it}^{\alpha} = \sum_{j \neq i} f_{ij} A_{jt} \tag{2}$$

where f_{ij} is the share of knowledge learned in state i.

Substituting equation (2) into equation (1) and by taking logs, equation (1) yields:

$$lnQ_{it} = \gamma lnA_{it} + \mu ln(\sum_{j \neq i} f_{ij} A_{jt}) \tag{3}$$

To denote the relative importance of external knowledge flows to in-state knowledge, f_{ijt} is standardized as $f_{ijt}{=}F_{ijt}/S_{jt} \Big/ F_{iit}/S_{it}$ where F is knowledge flows between the state of origin j and destination state, i (F_{ijt}) or flows within destination state (F_{iit}), while S is the in-state level of knowledge of the origin (S_{jt}) or destination (S_{it}) state. As we consider four channels through which knowledge is diffused, F is either traded patent flows, citation flows, inventor flows, or trade of goods, and S is in-state: innovation (proxied by number of patents) for the case of traded patent and citation flows, number of inventors for inventor flows, and gross domestic product (GDP) for trade of goods.

The empirical task of this paper is twofold. First, to estimate the determinants of knowledge flows (F_{ijt}) across the states of the US, and second, to assess the contribution of each flow on state's innovation production, as described by equation (3).

We use a gravity-like equation to model each type of flow. We indicate as F_{ij} the flows of knowledge generated in region j and learned in region i. Therefore, knowledge mobility across space depends on geographic and technological characteristics of the regional couple (i, j) as follows:

$$\begin{aligned} F_{ijt} = \delta_i + \delta_j + \delta_1 State\,Border_{ij} + \delta_2 Nearby\,States\,[500\,miles]_{ij} + \\ \delta_3 Distance\,[500 - 1,000\,miles]_{ij} + \delta_4 Distance\,[1,000 - 1,500\,miles]_{ij} + \\ \delta_5 Distance\,[1,500 - 2,000\,miles]_{ij} + \delta_6 Distance\,[2,000 - 2,500\,miles]_{ij} + \delta_7 Z_{ijt} + \epsilon_{ijt} \end{aligned} \tag{4}$$

where F_{ijt} is (one of the four) type of flows exchanged between two states i (destination) and state j (origin) at year t; δ_i and δ_j is origin and destination, respectively, state fixed effects; $State\,Border$ takes the value of 1 for flows exchanged between states i and j that share a common border and 0 otherwise; $Nearby\,States\,[500\,miles]$ takes the value of 1 for flows exchanged between states that do not share a common border and their geographical centers are located within a distance of 500 miles, and 0 otherwise; the generic term $Distance\,[\;]$ denotes various distance classes of 500 miles each and takes the value of 1 for flows exchanged between states i and j that are located within a certain 500 mile distance class, and 0 otherwise; vector Z contains controls relevant to technological proximity, and ϵ is an iid error term.

The coefficients δ_1 to δ_6 provide a characterization of how geographic factors shape flows exchanged across states. By model construction, each geographic coefficient captures the difference between knowledge flows diffused in geographic space to knowledge flows within a state. Consequently, the coefficient of the first dummy, $State\,Border$, captures how much less (more) knowledge exchange takes places between states that share a state border compared to in-state knowledge. For example, in the case of patent trade flows, δ_1 represents the difference between the flows of patents traded between two bordered states and patents traded within a state i. The second dummy, $Nearby\,States\,[500\,miles]$ captures the effect of geographic nearness of states, which do not share common borders, but are located in a vicinity of 500 miles, compared to in-state flows. Finally, each one of the coefficients of the rest of the distance dummies, examines whether states, located at a specific distance class, exchange less (more) flows in comparison to in-state interactions.[7] One would expect that increasing geographic distance would reduce exchange among states, signaling that knowledge flows are bounded in space and characterized by spatial declining effect.[8] The state border, additionally, tests the hypothesis that physical proximity between states that share a common border may affect knowledge flows irrespective of the distance.

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 differences may lead to an overestimation of the geography effect. Therefore, we also consider, along with the geographic proximity, technological and structural proximities between states - both included in the vector Z of equation (4). More specifically, technological distance, $TechnologicalDistance$, between two states i and j for a given year, t, is proxied as[9]:

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

One would expect regions with high technological activity are also those with most intense knowledge flows.

The similarity in the technological specialization of production sectors, $StructuralCloseness$, between two states i and j for a given year t is proxied by the (uncentered) correlation of their patent profiles and calculated as:[10]:

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

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

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.

2.2. *Estimation Strategy*

Our estimation strategy develops as follows: We jointly estimate, in a common system, patent trade flows, citation flows, inventor flows, and merchandise trade flows. As each flow is described by equation (4), we estimate a four-variate system of gravity-like equations. In doing so, we develop, for the first time in the literature, econometric techniques for multivariate non-linear seemingly unrelated regressions (SUR) for mixed count (citation, patent trade, and inventor flows) and continuous (trade of goods) responses, accounting for potential heterogeneity in the data. We apply Bayesian analysis and Markov Chain Monte Carlo (MCMC) methods for inference.

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[7]We opted for this distance taxonomy, i.e., batches of 500 miles, because the longest distance between two neighboring states is approximately 500 (517,705 miles to be precise), which is the distance between the centers of Colorado and Oklahoma. We proceed with the pace of 500 miles till we exhaust the distance between East and West Coast (approximately 2,500 miles). The proposed classification allocates about equal number of states in each distance class, meanwhile keeping the number of classes as low as possible. Alternative division of geographic space is not expected to modify results in any significant way.

[8]The localization of knowledge flows has been considerably tested in the spillover literature, which has unanimously documented the geographic confinement of knowledge diffusion (Jaffe et al., 1993; Peri, 2005; Thompson, 2006; Alcacer and Gittelman, 2006; Belenzon and Schankerman, 2013).

[9]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).

[10]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. Hall et al. (2001) had categorized US classifications in 36 broad technology fields; however, in the 2006 NBER update, there was an addition of a 37th technology field in the area of Computers and Communication Technologies. 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.

Merchandise trade data are available, however, for limited number of years. For robustness purposes, we estimate in a common system only the count variables - patent trade flows, citation flows and inventor flows. A first candidate model to jointly estimate these flows is the non-linear seemingly unrelated (SUR) Poisson model, introduced by King (1989). A serious limitation of this model, however, is its inability to account for over-dispersion or extra-Poisson variation in the data. Winkelmann (2000) proposes an alternative model, which does not abandon the basic convolution structure of the seemingly unrelated Poisson, but rather generalizes some of its assumption to allow for over-dispersion in count data. The proposed model has negative binomial marginals and is referred to as seemingly unrelated negative binomial model. We extend the work of Winkelmann (2000) and apply Bayesian analysis and MCMC techniques as developed in Tsionas (1999, 2001) to further account for potential unobserved heterogeneity in the data. We, therefore, estimate a tri-variate system of seemingly unrelated negative binomial regressions allowing for unobserved heterogeneity.

As an exercise and in comparison to the literature, we also estimate single (univariate) equations for each channel of knowledge flows: for traded patent, citation, inventor, and trade flows. We use negative binomial estimation techniques for the first three flows and OLS with state and year fixed effects for the trade of goods.[11]

Finally, having estimated knowledge flows that operate via our different channels, we are able to assess the importance of each channel of knowledge diffusion in the production of local innovation as described by equation (3).

The next two sub-sections describe the SUR methodologies.

2.2.1. Multivariate Negative Binomial Regressions

We introduce multivariate negative binomial regressions along with techniques for statistical inference. Our point of departure is Winkelmann (2000). To summarise Winkelmann's approach suppose $y_i = [y_{i1}, ..., y_{iM}]'$ is an $M \times 1$ vector of count variables, for a particular observation, $i = 1, ..., n$. For a single count variable, say y_i, is well-known that the negative binomial (NB) specification arises from the Poisson if we assume: $y_i|v_i \sim \text{Po}(\lambda v_i)$ and $v_i \sim \text{Ga}(\alpha, \alpha)$, where "Po" denotes the Poisson and "Ga" the Gamma distribution. Then, it can be shown that y_i follows a NB distribution with mean λ and variance $\lambda + \alpha^{-1}\lambda^2$. In the multivariate context, Winkelmann (2000) proposes the following model:

$$y_i = y_i^* + u_i \iota_M \tag{5}$$

where the scalar random variable u_i follows a NB, ι_M is a vector of ones in $\Re^M$ and:

$$y_{im}^*|v_{im} \sim \text{Po}\left(\lambda_{im} v_{im}\right), v_{im} \sim \text{Ga}\left(\alpha, \alpha\right), m = 1, ..., M$$

For u_i, the NB assumption leads to the formulation:

$$u_i|v_{io} \sim \text{Po}\left(\lambda_{io} v_{io}\right), v_{io} \sim \text{Ga}\left(\gamma, \gamma\right)$$

One can introduce covariates by assuming:

$$\lambda_{im} = \exp\left(x_i'\beta_m\right), m = 1, ..., M$$

where x_i is a $k \times 1$ vector and λ is the mean of the data and latent variable. Using the re-parametrization $\mu_{im} = \lambda_{im}/\sigma$, the mean remains the same and the variance becomes $\text{Var}\left(y_{im}^*\right) = \lambda_{im}\left(1 + \sigma\right)$. The covariance matrix of y_i is $\text{Cov}\left(y_i\right) = \left(\Lambda_i + \gamma \iota\iota'\right)\left(1 + \sigma\right)$, where $\Lambda_i = diag[\lambda_{i1}, ..., \lambda_{im}]$.

Relative to the multivariate Poisson distribution there is an over-dispersion parameter given by $1 + \sigma$ and as $\sigma \to 0$ the distribution approaches the multivariate Poisson.

Unlike Winkelmann (2000), we introduce further unobserved heterogeneity in the following form:

[11]Negative Binomial estimation is also used in similar to ours contexts (Peri, 2005; Perkins and Neumayer, 2011; Furman and Stern, 2011).

$$\log \lambda_{im} = x_i'\beta_m + \epsilon_{im}, m = 1, ..., M \tag{6}$$

where $\epsilon_i \sim N_M(0, \Sigma)$.

Parameter estimation in multivariate count data models can be complicated using standard classical analysis. In Bayesian approach, the unknown parameters are assumed to be random variables. Data augmentation techniques can estimate both parameters of interest and nontrivial variables such as latent. The likelihood functions of count models may contain many integrals, which often makes frequentist approaches difficult or even unfeasible. An advantage of the Bayesian approach using MCMC is that one only has to consider the likelihood function conditional on the unobserved variables, which, in many cases, implies that Bayesian parameter estimation is faster than classical maximum likelihood estimation.[12]

Coupled with a prior $p(\beta)$, the augmented likelihood is a Bayesian posterior (kernel) density. Contrary, for example, to Winkelmann's likelihood functions for negative binomial models, our posterior is not available in closed form, as it involves integrals with respect to the unobserved latent variables (e.g., λ and error terms) that cannot be computed in closed form.[13] The reason is that we allow for *unobserved* heterogeneity in λ, which is not the case in Winkelmann (2000). We feel that this is an important generalization, because unobserved heterogeneity is commonly encountered in count data models and also leads to more flexible models by allowing (statistical) mixing, which is not possible when only observed heterogeneity is taken into account.

We write the augmented likelihood function of y_i conditional on all latent variables $\mathcal{U}_i = (v_i, u_i, \lambda_i)$ and parameters, $\theta = (\beta, \lambda, \sigma)$, of the model as follows:

$$\begin{aligned} p(y_i|\mathcal{U}_i, \theta) = \tfrac{\alpha^{\alpha M}}{\Gamma(\alpha)^M} \textstyle\prod_{m=1}^M \left\{ \exp\left(-\lambda_{im}v_{im}\right) \tfrac{(\lambda_{im}v_{im})^{y_{im}+u_i}}{(y_{im}+u_i)!} v_{im}^{\alpha-1} \exp\left(-\alpha v_{im}\right) \right\} \\ \tfrac{\gamma^\gamma}{\Gamma(\gamma)} \exp\left(-\lambda_{io}v_{io}\right) \tfrac{(\lambda_{io}v_{io})^{u_i}}{u_i!} v_{io}^{\gamma-1} \exp\left(-\gamma v_{io}\right) \\ (2\pi)^{-m/2} |\Sigma|^{-1/2} \left\{ \textstyle\prod_{m=1}^M \lambda_{im}^{-1} \right\} \exp\left\{ -\tfrac{1}{2} \left(\log \lambda_i - X_i\beta\right)' \Sigma^{-1} \left(\log \lambda_i - X_i\beta\right) \right\} \end{aligned} \tag{7}$$

where $X_i = I_M \otimes x_i'$, $\beta = \left[\beta_1', ..., \beta_M'\right]'$ and $\lambda = \left[\lambda_1', ..., \lambda_M'\right]'$.

The first line is the joint distribution of λ_{im} and v_{im} ($m = 1, ..., M$) conditional on u_i, the second line provides the distribution of u_i, while the third line gives the distribution of λ_i conditional on the observed covariates.

The posterior distribution of the parameters is given by:

$$\begin{aligned} p\left(\theta|y\right) = \textstyle\prod_{i=1}^n \int p\left(y_i|\mathcal{U}_i, \theta\right) d\lambda_i = \prod_{i=1}^n \int \{ \tfrac{\alpha^{\alpha M}}{\Gamma(\alpha)^M} \prod_{m=1}^M \left\{ \exp\left(-\lambda_{im}v_{im}\right) \tfrac{(\lambda_{im}v_{im})^{y_{im}+u_i}}{(y_{im}+u_i)!} v_{im}^{\alpha-1} \exp\left(-\alpha v_{im}\right) \right\} \\ \tfrac{\gamma^\gamma}{\Gamma(\gamma)} \exp\left(-\lambda_{io}v_{io}\right) \tfrac{(\lambda_{io}v_{io})^{u_i}}{u_i!} v_{io}^{\gamma-1} \exp\left(-\gamma v_{io}\right) \\ (2\pi)^{-m/2} |\Sigma|^{-1/2} \left\{ \textstyle\prod_{m=1}^M \lambda_{im}^{-1} \right\} \exp\left\{ -\tfrac{1}{2} \left(\log \lambda_i - X_i\beta\right)' \Sigma^{-1} \left(\log \lambda_i - X_i\beta\right) \right\} \} d\lambda_i \end{aligned} \tag{8}$$

Before proceeding it is perhaps worthwhile to explain the basics of our estimation and inference techniques. Properly defined and implemented, MCMC methods enable the user to successively sample values from a convergent Markov chain, the limiting distribution of which is the true joint posterior of the model unobservables (steady-state of the chain). Given a posterior distribution of parameters θ, $p(\theta|y) \propto L(\theta; y)p(\theta)$, where y is the data, $L(\theta; y)$ is the likelihood and $p(\theta)$ is the prior, we draw a large (non-random) sample S so that $\left\{\theta^{(s)}\right\}_{s=1}^S \to p(\theta|y)$ in distribution. It is perhaps important to mention that

[12]In standard classical approach, the likelihood function has to be transformed into unconditional distributions by integrating out the non-trivial variables (such as latent); a task which can be complicated and hard in the case of multidimentional integrals. MCMC simulation techniques can be powerful in estimating such models.

[13]A technical Appendix can be provided upon request.

the conditional posterior distribution of λ is log-concave to efficient numerical procedures can be used to generate random drawings from the distribution. This requires finding the mode and numerical Hessian at each MCMC iteration. In practice, this is quite easy by application of a simple quasi-Newton algorithm (Wild and Gilks, 1993). The draws for $\theta^{(s)}$ are generated sequentially so the optimization problem can be reduced to a series of rather simple univariate optimization problems. Conditional posteriors for β and covariance matrix are in standard families (multivariate normal and Wishart, respectively) so random number generation is straightforward.[14]

We take as parameter estimates the posterior mean $\bar{\beta} = E(\beta|y) \simeq S^{-1} \sum_{s=1}^{S} \beta^{(s)}$. Standard errors are computed from a Newey-West type autocorrelation-consistent covariance matrix of $\left\{\beta^{(s)}\right\}_{s=1}^{S}$ (using 10 lags) to deal with inherent autocorrelation of the posterior draws induced by MCMC methods.

Priors are defined as follows. For regression parameters, we assume the prior of β is diffuse, that is $p(\beta) \propto$ const. For the $M \times M$ covariance matrix Σ we assume a non-informative, improper, prior of the form $p(\Sigma) \propto |\Sigma|^{-(M+1)/2}$. These priors are "uninformative" in the sense that they let the likelihood dominate the prior and, therefore, our results are not driven by the prior specification. In initial experimentations, we imposed normal but relatively flat priors of the form $\beta \sim N(0, h^2 I)$, with 0 and I vector of zeros and matrix, respectively, and h ranging from 1 to 100, but did not notice any significant different in the final posterior results.

To implement the MCMC algorithm, we use a total of 500,000 iterations and use the first B as a burn-in period; that is the first B samples, $\{\theta^0, \theta^1, ..., \theta^B\}$, are discarded. The value of B is decided based on Geweke (1992) convergence diagnostic and ranged from 15,000 to 35,000 iterations in our applications. Due to the large sample size, the effect of the prior is negligible.

Therefore, we estimate equation (6) for the case of three count variables, i.e., patent trade, citation, and inventor flows (tri-variate seemingly unrelated negative binomial regressions):

$$\log \lambda_{im} = x_i' \beta_m + \varepsilon_{im}, \ \ m = 1, 2, \ and \ 3 \tag{9}$$

where x_i' is the vector of geographic and technological factors as defined in equation (4), β the vector of the corresponding coefficients, and ϵ the error term.

2.2.2. Mixed Count and Continuous Responses

Suppose that we have an additional $R \times 1$ vector of responses, y_{ir}, $r = M+1, ..., M+R$. The most reasonable way to handle the matter in the multivariate situation is to extend (6) in the following form:

$$\begin{aligned} \log \lambda_{im} = x_i' \beta_m + \varepsilon_{im}, \ \ m = 1, ..., M \\ y_{ir} = x_i' \beta_r + \varepsilon_{ir}, \ \ r = M+1, ..., M+R \end{aligned} \tag{10}$$

We redefine $\epsilon_i = [\epsilon_{i1}, ..., \epsilon_{iM}, \epsilon_{i,M+1}, ..., \epsilon_{i,M+R}]'$ and assume:

$$\epsilon_i \sim N_{M+R}(0, \Sigma)$$

where Σ is an $(M+R) \times (M+R)$ covariance matrix.

The major change in the distribution of observables $p(y_i|U_i, \theta)$ is in the third line of equation (7), which should now be:

$$(2\pi)^{-m/2} |\Sigma|^{-1/2} \left\{ \prod_{m=1}^{M} \lambda_{im}^{-1} \right\} \exp \left\{ -\tfrac{1}{2} \left(\Psi_i - X_i \beta\right)' \Sigma^{-1} \left(\Psi_i - X_i \beta\right) \right\}$$

where $\Psi_i = \left[\log \lambda_i', y_{i,M+1}, ..., y_{i,M+R}\right]'$.

[14] The exact details of the algorithm are very similar to the ones reported in Tsionas (2001) for the case of multivariate Poisson regression with unobserved heterogeneity and, thus, are not reported here.

The posterior distribution of the parameters is given by:

$$p(\theta|y) = \prod_{i=1}^{n} \int p(y_i|\mathcal{U}_i,\theta)\, d\lambda_i = \prod_{i=1}^{n} \int \Big\{ \frac{\alpha^{\alpha M}}{\Gamma(\alpha)^M} \prod_{m=1}^{M} \left\{ \exp\left(-\lambda_{im} v_{im}\right) \frac{(\lambda_{im} v_{im})^{y_{im}+u_i}}{(y_{im}+u_i)!} v_{im}^{\alpha-1} \exp\left(-\alpha v_{im}\right) \right\}$$
$$\frac{\gamma^{\gamma}}{\Gamma(\gamma)} \exp\left(-\lambda_{io} v_{io}\right) \frac{(\lambda_{io} v_{io})^{u_i}}{u_i!} v_{io}^{\gamma-1} \exp\left(-\gamma v_{io}\right)$$
$$(2\pi)^{-m/2} |\Sigma|^{-1/2} \left\{ \prod_{m=1}^{M} \lambda_{im}^{-1} \right\} \exp\left\{ -\frac{1}{2} \left(\Psi_i - X_i\beta\right)' \Sigma^{-1} \left(\Psi_i - X_i\beta\right) \right\} \Big\} d\lambda_i \tag{11}$$

Bayesian analysis for the multivariate Poisson regression model, developed by Tsionas (2001) can be applied in this case, as well. The analysis is organized around MCMC methods for inference, as outlined above.

We, therefore, estimate equation (10) for three count variables, patent, citation and inventors' mobility flows, and one continuous, trade flows (four-variate mixed system of count and continuous responses):

$$\begin{aligned} \log \lambda_{im} &= x_i'\beta_m + \varepsilon_{im}, \ m = 1,2,3 \\ y_{ir} &= x_i'\beta_r + \varepsilon_{ir}, \ r = 1 \end{aligned} \tag{12}$$

where x_i' is the vector of geographic and technological factors as defined in equation (4), β the vector of the corresponding coefficients, and ϵ the error term.

3. Data Description and Analysis

Our empirical analysis is based on 48 states of the US for the period 1993 to 2006.[15] Data are obtained from a range of sources.

Patent trade data come from a newly compiled dataset, kindly offered to us, by the office of the Chief Economist of the United States Patent and Trademark Office (USPTO) referred as Patent Assignment Dataset. The latter, contains assignments (transactions) of US issued patents between entities registered at the USPTO.[16] A typical assignment is characterized by a unique identifier (i.e., reel frame), the names of the buyer (i.e., assignee) and seller (i.e., assignor), the date that the transaction agreement was signed (execution date), and the patent numbers or patent applications that are traded per assignment.[17] Employing assignment data to construct a patent dataset, we faced two main challenges. The first relates to the fact that entities are not required to disclose transactions to the USPTO. However, for legal and perhaps accounting reasons, they have incentives to do so.[18] A challenge associated with assignment data is that it is still likely that a number of transactions have not been disclosed to the USPTO due to negligence or to strategic behavior. However, we do not expect this to be systematic for aggregated transactions across geographical areas. An additional challenge is associated with excluding 'routine' transactions. In the US, only an individual can file for a patent application. Subsequently, this individual may re-assign the patent to her firm or institution where she is employed. These transactions are also included to the dataset. Thus, the challenge here is to isolate the economically meaningful re-assignments and discard otherwise.

Taking these two challenges into consideration, we end up having 128,578 patents, issued between 1988 and 2006 and traded from 1993 to 2006 between US located entities. These patents are associated with 65,558 transactions for which we have address information for both the assignor and assignee. However, transactions may contain more than one patents and a patent may be transacted more than once as there is a many-to-many relationship between patents and transactions. To construct the flows of patent trades, we aggregate the number of patents that have been traded from entities located in the origin state to entities

[15] The states of D.C., Alaska, and Hawaii are not included in our analysis due to limited data information.

[16] In the US, when entities transfer US issued patents to other entities, they disclose such transactions to the USPTO. The latter are called assignments.

[17] There is also a field in the assignment data in which entities can disclose the justification for the transfer. However, the justification, in most cases, is a generic one (i.e. assignment of assignor's interest) and it is rather difficult to extract information from that field.

[18] For instance, in a potential litigation the courts will need to know clearly which firm or organization holds the intellectual property in question. Thus, parties that are involved in such transactions have incentives to disclose such information to the USPTO.

located in destination state for every year. For patents, which are traded more than once, each transaction is registered as a new transaction and, therefore, counted accordingly.[19]

Patents contain references to prior patents and the scientific literature.[20] Patent citation data originate from the National Bureau of Economics Research (NBER) *Patent Data Project*, which is publicly available and described in detail by Hall et al. (2001).[21] The database contains citations of all US issued patents up to 2006. We construct citation flows for the period 1993-2006 by counting citations made from 1993 to 2006 to all US patents issued from 1988 to 2006.[22] In constructing citation flows across states, we consider the location of the patent owner, which is written on the patent document wrapper for both (citing and cited) patents.

Information on inventors' mobility, defined as the number of firms or states a patent inventor changes during his lifetime every time he files for a new patent, is obtained from the Disambiguation and Co-authorship Networks of the U.S. Patent Inventor Database, which is publicly available and described in detail by Lai et al. (2011).[23] An occurrence of inventor mobility is counted only if an inventor files for a patent either under a different owner (firm) or under the same owner but in different state. We construct inventors' mobility flows by counting the number of occurrences in every year.

Merchandise trade flows at the state level are extracted from the Bureau of Transportation Services *Commodity Flow Surveys*. Data are available only for the years 1993, 1997, and 2002.[24]

Finally, data on geographic characteristics of the states as well as data to construct technological and structural closeness are obtained from the following sources. The geographic distance (in miles) between two states is the distance between each state's geographical center as the crow flies. This information is obtained from Google Maps.[25] Information on a state's R&D expenditure and number of scientists (science, engineering, and health researchers) to construct the technological effort of a state, is extracted from the National Science Foundation *Science and Engineering State Profiles*. Using state-level R&D spending and the perpetual inventory method as in Guellec and van Pottelsberghe de la Potterie (2004), we construct R&D stocks, using a 10% depreciation rate, to estimate elasticities in the innovation function.[26] Further, to construct the index of structural proximity, we need to allocate patents into different technological fields. Patents' primary US Classifications are retrieved from the NBER.

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

[19]For patents traded more than once, and for robustness purposes, we construct two alternative measures of traded patent flows. The first is called, 'first flow' and considers, for each patent, only its first assignment, ignoring the rest of its transactions. The second measure is called 'last flow' and for each patent excludes all the intermediate transactions and records only the assignment between the first and last entity. For example, for a certain patent which is sold from California to New York state and then from New York state to Texas, the measure 'all flows' registers both transactions, while the other two measures register only one transaction: 'first flow' registers the transaction between California to New York state, and 'last flow' registers the one between California to Texas.

[20]The USPTO patents report citations in the front page of the patent document. There may be citations to patents and non-patent literature embedded in the text of the patent document.

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

[22]We also distinguish citations into citations of traded patents and citations of non-traded patents and, accordingly, construct citation flows of traded patents and citation flows of non-traded patents. Information about the nature of a patent, i.e., whether it is traded or not, is retrieved from the USPTO.

[23]Information on the data is provided at http://hdl.handle.net/1902.1/15705 UNF:5:9kQaFvALs6qcuoy9Yd8uOw== V1.

[24]What is only available is the value of state's total imports; there is no information, however, by type of (imported) good.

[25]See http://www.freemaptools.com.

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

Table 1: Summary Statistics

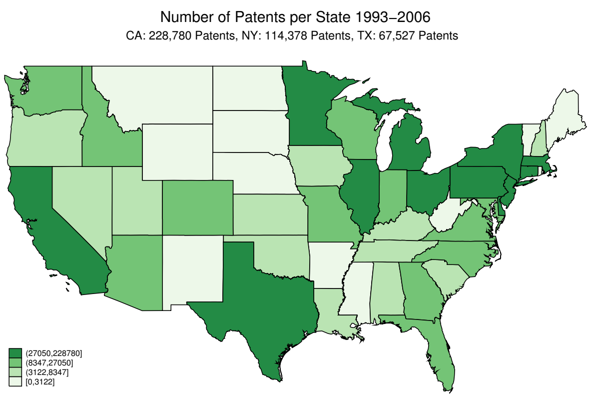
variables	Observations	Mean	St. Dev.	Min	Max
Patent Trade Flows	32,256	4.71	41.63	0	3,262
Citation Flows	32,256	210.76	1,316.56	0	85,287
Inventor Flows	32,256	13.07	174.01	0	10,669
Trade Flows	6,227	3,396.93	16,467.95	0.96	535,263
State Border	2,256	0.10	0.29	0	1
Nearby States [500 *miles*]	2,256	0.12	0.32	0	1
Distance $[500 - 1,000\, miles]$	2,256	0.32	0.47	0	1
Distance $[1,000 - 1,500\, miles]$	2,256	0.25	0.43	0	1
Distance $[1,500 - 2,000\, miles]$	2,256	0.13	0.34	0	1
Distance $[2,000 - 2,500\, miles]$	2,256	0.08	0.27	0	1
TechnologicalDistance	32,256	0.63	0.50	0	3
StructuralCloseness	32,256	0.70	0.18	0.05	1

Note: *Patent Trade Flows*, *Citation Flows* (of traded and non-traded patents), and *Inventor Flows* are occurrences (non-negative integers); merchandise *Trade Flows* are in millions of constant (2000) US dollars, *State Border* is dummy (1 if states for common border, 0 otherwise), the generic term *Distance* [ ] refers to different distance classes of 500 miles each and is a dummy (1 if states are located within the class, 0 otherwise); *TechnologicalDistance* ranges from 0 (similar) to 3 (dissimilar), and *StructuralCloseness* ranges from 0 (dissimilar) to 1 (similar).

According to Table 1, states, on average, trade about 5 patents per year and exchange about 211 citations, with citation flows associated with traded patents to comprise 17% of total citation flows. On average, states trade, per year, goods of 3.4 billion dollars value. For every pair of states, in a given year, there are, on average, 13 occurrences of inventors' mobility. Each pair of states is, on average, 10% likely to be neighboring with each other. Furthermore, 12% of all possible pairs of states are closer than 500 miles and do not share common state border, 32% are located in a distance of 500 to 1,000 miles, 25% in a distance of 1,000 to 1,500 miles, 13% between 1,500 and 2,000 miles and 8% within a range of 2,000 to 2,500 miles. 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 innovation (number of patents) in the US for the period 1993-2006.

Figure 1: Patent Production in the US



As Figure 1 shows, intense patenting activity is concentrated in few states in the US, mainly in East and West Coasts along with some states around the Great Lakes. Specifically, more than 60% of total production of patents takes place in five states: California (CA), New York (NY), Texas (TX), Illinois (IL), and New Jersey (NJ). The least involved states in producing innovation are Alaska (AK), Hawaii (HI), the Dakotas (ND & SD), and Wyoming (WY).

Summary statistics per state, reported in Table A.1 in the Appendix, reveal a large variety of patterns. However, a consistent finding that emerges is that states, which are top ranked in producing patents, are also high performers in terms of trading patents and goods, exchanging citations, and mobility of inventors, with California (CA) to be by far an outstanding performer.

4. Empirical Results

This section presents our results. First, we examine whether proximity shapes the mobility of knowledge flows and, second, whether knowledge flows have an effect on local innovation production.

4.1. How Important is Proximity for Knowledge Mobility?

Table 2 reports the results. Columns (i) to (iv) report univariate (single-equation) estimates of equation (4) for traded patent ($PatentFlows$), citation ($CitationFlows$), mobility of inventors ($InventorFlows$), and trade ($GoodsFlows$) flows, respectively. Then, column (v) reports Negative Binomial estimates of jointly estimated count flows as described by the tri-variate SUR in equation (9). Lastly, column (vi) reports estimated coefficients of the joint estimation of all four flows as described by the SUR of mixed count and continuous responses in equation (12) for the years 1993, 1997, and 2002. Standard errors are reported in parentheses.

As one notes, single equation estimates are, in most cases, similar to their SUR counterparts. However, the standard errors of both SUR models are smaller than those of the single equations for almost all parameter estimates, which is a clear indication of increased efficiency of the system over single equation estimates. Our discussion, therefore, is based on SUR estimates.[27]

Each geographic coefficient in Table 2 captures the difference between knowledge flows diffused in geographic space to knowledge flows within a state, which is the benchmark flow by model construction. To convert each value to percentage change, we use the exponential formula. Beginning with column (v), the coefficient of $State\ Border$ for the case of patent citation flows implies that states which share common border exchange about 76% (= $e^{-1.42}$) less citations to what they would exchange within their borders. In other words, on crossing a state border, knowledge based on citation flows diminishes to about 24% (= $1 - e^{-1.42}$). Irrespective of border, distance also shapes knowledge flows that operate via patent citations. Knowledge on crossing nearby but not adjacent states diminishes to 21% (= $e^{-1.55}$) to its in-state level as the coefficient of $Nearby\ States\ [500 miles]$ indicates. On average, an additional reduction of 1.75% takes place for each 500 miles traveled; however, when distance becomes larger than 2,000 miles, knowledge flows increase, compared to the flows exchanged in previous distance intervals, by almost 8%. This seemingly controversial finding is due to large citation exchange between East and West ('California effect') Coast as states in these coasts are among the top innovation performers in the US. Overall, results show that knowledge spillovers based on citation flows are restricted by state border and geographic distance.

[27] Before embarking on discussing our findings, we perform a number of tests. First, we test whether single-equation coefficients in each type of flow (i-iv) are all simultaneously zero. The value of the Wald test ($\chi^2(115)$) is 10,928.76 for trade patent flows, 272,080.70 for citation flows, and 69,083.07 for inventor flows. For the trade of goods, the value of the statistic $F(104, 6122)$ is 750.7. We, therefore, reject the null hypothesis of all coefficients in each equation (i-iv) to be simultaneously all zero. Second, we test whether coefficients across different flows in each SUR model are all equal to each other and to zero. Tests support that they are different from zero in both SUR models. The value of $\chi^2(104)$ for the tri-variate is 4,590 and for the four-variate $\chi^2(115)$ is 5,790; therefore, we reject the null hypothesis of coefficients equality to zero. Lastly, we test for equality of coefficients between single and multivariate (SUR) approaches. Test results support that univariate estimated coefficients are different from their multivariate counterparts. To test for the equality of the coefficients between single equation and SUR, we let p to be a set of coefficients from SUR and p_0 the counterpart set from the single equation estimates. Then, we define d to be equal to $p - p_0$. Suppose V to be the covariance of d, then $d'(V)^{-1}d \sim \chi^2$. The values of $\chi^2(115) = 88.91$ and $\chi^2(104) = 117.67$ of tri-variate and four-variate SUR, respectively, indicate that univariate estimates are different from their multivariate counterparts.

Table 2: Determinants of Knowledge Flows in the US

	Sigle Equation Estimates[(I)]				**Tri-variate SUR Estimates**[(II)]			**Four-variate SUR Estimates**[(III)]			
	Citation flows[a]	*Patent flows*[b]	*Inventor flows*[c]	*Trade flows*[d]	*Citation flows*[a]	*Patent flows*[b]	*Inventor flows*[c]	*Citation flows*[a]	*Patent flows*[b]	*Inventor flows*[c]	*Trade flows*[d]
	(i)	(ii)	(iii)	(iv)		(v)			(vi)		
State Border	-1.66***	-3.01***	-4.42***	-2.26***	-1.42***	-2.31***	-3.71***	-1.31***	-2.25***	-3.77***	-2.25***
	(0.043)	(0.122)	(0.038)	(0.083)	(0.001)	(0.002)	(0.004)	(0.001)	(0.008)	(0.010)	(0.010)
Nearby States [500 *miles*]	-1.76***	-3.59***	-5.13***	-3.25***	-1.55***	-2.58***	-4.07***	-1.48***	-2.45***	-4.27***	-3.23***
	(0.043)	(0.122)	(0.037)	(0.080)	(0.001)	(0.003)	(0.006)	(0.001)	(0.009)	(0.016)	(0.016)
Distance $[500-1,000\ miles]$	-1.87***	-3.75***	-5.41***	-3.96***	-1.59***	-2.66***	-4.19***	-1.46***	-2.52***	-4.60***	-3.94***
	(0.043)	(0.125)	(0.036)	(0.079)	(0.001)	(0.002)	(0.004)	(0.001)	(0.006)	(0.010)	(0.011)
Distance $[1,000-1,500\ miles]$	-1.99***	-4.05***	-5.65***	-4.58***	-1.67***	-2.74***	-4.26***	-1.52***	-2.59***	-4.55***	-4.57***
	(0.043)	(0.142)	(0.040)	(0.081)	(0.002)	(0.003)	(0.004)	(0.001)	(0.010)	(0.009)	(0.009)
Distance $[1,500-2,000\ miles]$	-2.06***	-4.06***	-5.73***	-4.91***	-1.77***	-2.76***	-4.32***	-1.64***	-2.62***	-4.51***	-4.89***
	(0.044)	(0.134)	(0.041)	(0.083)	(0.001)	(0.003)	(0.006)	(0.001)	(0.011)	(0.013)	(0.012)
Distance $[2,000-2,500\ miles]$	-1.88***	-4.24***	-5.64***	-4.98***	-1.45***	-2.74***	-4.30***	-1.29***	-2.64***	-4.30***	-4.97***
	(0.044)	(0.134)	(0.043)	(0.088)	(0.001)	(0.002)	(0.003)	(0.001)	(0.006)	(0.008)	(0.008)
TechnologicalDistance	-0.14***	-0.29***	-0.33***	-0.13***	-0.04***	-0.25***	-0.33***	0.09***	-0.22***	-0.84***	-0.13***
	(0.012)	(0.078)	(0.019)	(0.023)	(0.001)	(0.002)	(0.004)	(0.001)	(0.008)	(0.010)	(0.010)
StructuralCloseness	1.19***	1.07***	0.60***	0.03	0.25***	0.78***	0.11***	1.02***	0.76***	0.82***	0.05***
	(0.048)	(0.195)	(0.063)	(0.093)	(0.000)	(0.006)	(0.011)	(0.001)	(0.024)	(0.029)	(0.030)
Observations	32,256	32,256	32,256	6,227	32,256	32,256	32,256	6,227	6,227	6,227	6,227

All regressions include time dummies and origin and destination state fixed effects. Standard errors are reported in parentheses (heteroskedastic robust standard errors only for the single equation estimates); Coefficients of *Constant* term are omitted; *State Border* takes the value of 1 for flows exchanged between neighbor states (share common border) i and j and 0 otherwise; *Nearby States* [500 *miles*] takes the value of 1 for flows exchanged between states that do not share a common border and their geographical centers are located within a distance of 500 miles, and 0 otherwise; *Distance* $[500-1,000\ miles]$, *Distance* $[1,000-1,500\ miles]$, *Distance* $[1,500-2,000\ miles]$, and *Distance* $[2,000-2,500\ miles]$ are distance classes of 500 miles each and take the value of 1 for flows exchanged between states i and j that are located within 500 to 1,000, 1,000-1,500, 1,500-2,000, and 2,000-2,500 miles, respectively, and 0 otherwise; *TechnologicalDistance* is the degree of proximity of the technological effort (*R&D/Scientists*) of states i and j; *StructuralCloseness* is the degree of technological similarity of technological specialization in production sectors of states i and j; (***): significance at 1% level.

[I] Specification (I) reports single-equation (univariate) negative binomial (columns i, ii, and iii) and OLS (column iv) estimates.

[II] : Specification (II) reports negative binomial estimates of tri-variate SUR (column v).

[III] : Specification (III) reports estimates of four-variate SUR of mix count and continuous responses (column vi) for the years 1993, 1997, and 2002.

[a] *CitationFlows* are citation flows.

[b] *PatentFlows* are patent trade flows.

[c] *InventorFlows* are inventor flows.

[d] *TradeFlows* are merchandise trade (imports) flows.

The effect of geography is even more pronounced on the flows of traded patents. Compared to citation flows, the volume of patent trades which transcends a state border is 1.5 times smaller and 3 times more constrained in space. Specifically, when knowledge, based on patent trade flows, crosses a state border, is reduced to 10% (= $1 - e^{-2.31}$) compared to in-state knowledge exchange. Significant flow reduction takes place already within a distance of 500 miles as only 7.6% (= $1 - e^{-2.58}$) of its in-state level crosses that distance and any further increase of distance decreases knowledge flows by 0.5%. As in the case of citation flows, when distance becomes larger than 2,000 miles, there is a slight increase of patent trade flows of 0.4%, compared to the average effect of all previous distance intervals, due to East-West Coast patent trade. In sum, the decay of knowledge flows, based on patent trade flows is sharper than that of citation flows. The potential need for the patent buyer to acquire information or keep some contact with the patent owner attaches a pronounced role to geography in shaping patent trade than patent citation flows.

Geography, however, appears to exert the heaviest toll on inventors' migration flows. Indicative of the strong border effect on this type of flows is the last set of estimates of column (v), which reveal that only 2.4% (= $1 - e^{-3.71}$) of knowledge carried by inventors crosses a state border. Moreover, 1.7% (= $1 - e^{-4.07}$) of knowledge embodied in inventors crosses the vicinity of 500 miles and this percentage remains unaltered for any farther traveled distance implying that the die-out effect is large and sharp. There is an increase of inventor migration flows after a distance of 2,000 miles, as the research-facilitating environments of California and East Coast act as attractors of high quality scientists; nevertheless the effect is diminutive.

In sum, geographic proximity plays an important role in shaping flows, in particular, flows that are generated from market mechanisms. Nevertheless, states located close to each other may exchange more knowledge with each other simply due to the technological effort they pour and/or technological specialization in their production structure. As our results show, a one unit decrease in technological effort distance, $TechnologicalDistance$, between states, increases the exchange of flows between states from 4% (citation flows) up to 28% (inventor flows) indicating that technological proximity between states is more essential to the market-based knowledge flows, particularly to inventor flows. As the literature stresses, investment in R&D and human capital makes a region attractive to talented individuals Lucas (1988). Furthermore, a state receives more flows from a state with technological sector specialization as itself than from a state with completely dissimilar technological specialization production structure. Specifically, a unit increase in structural similarity, $StructuralSimilarity$, between states, increases the exchange of flows from 12% (inventor flows) up to 118% (patent trade flows). It appears that technological specialization matters more for disembodied knowledge flows that operate via traded patents and patent citations, as researchers are expected to benefit more from other researchers who work in the same or related technologies (Bode, 2004; Peri, 2005).

We now extend our analysis to including one more market-based channel of knowledge flows, that of merchandise trade. Results are remarkably stable, as estimates of the four-variate SUR reported in column (vi) of Table 2 are similar to their counterparts, reported in column (v), despite of the large sample reduction. On crossing a state border, knowledge flows, embodied in physical trade, diminishes to 10% (= $1 - e^{-2.26}$) to in-state trade. Irrespective of border, distance, on average, diminishes trade flows to about 2% (= $1 - e^{-4.32}$, where -4.32 is the mean of the five distance classes). The California effect, while discernible to all flows, is absent for the trade of goods. Other types of proximities, such as technological effort and production specialization similarities, continue to also shape this type of flow. Through the channel of goods trade, a unit increase of technological effort similarity between two states increases trade by 12%. In addition, a state receives 5% more knowledge from a state with the same technological specialization as itself, than from a state with dissimilar technological specialization.[28]

[28] A large volume of literature has documented the negative impact of geographic distance and borders on the flows of physical trade (McCallum, 1995; Wolf, 2000; Chen, 2004). To compare with the trade literature, we drop technological proximity from the four-variate system. The geographic effect, in this case, becomes, as expected, somewhat stronger by approximately 0.3% (trade estimates of $State\ Border$, $Nearby\ States[500miles]$, $Distance[500-1,000miles]$, $Distance[1,000-1,500miles]$, $Distance[1,500-2,000miles]$, and $Distance[2,000-2,500miles]$ are: -2.33 (0.008), -3.33 (0.015), -4.04 (0.007), -4.67 (0.005), -4.99 (0.011), and -5.05 (0.005), respectively. Number in parentheses are standard errors). Our estimates, although not directly comparable, corroborate with evidence provided in the trade literature about the home bias effect within the US states (Wolf, 2000).

Taken together with our earlier results, localization bias on the state level appears to be quite sturdy for all kinds of knowledge flows. Therefore, the general finding of geographic localization of flows documented in the literature also finds support in this study. However, the very significant impact of border and distance on knowledge flows based on ideas (traded patent and citation flows) across states of the US is at first sight quite surprising and puzzling: unlike goods and inventors, ideas are weightless, and distance cannot just proxy transportation costs. Instead, distance and border could be seen as informational barriers, and serve as proxies for all types of informational frictions. Agents within a state tend to know much more about each other and each other's business and technologies, either because of direct interactions between their citizens or because of better media coverage. Consequently, distance and border act as barriers to social connectedness, micro-cultural affinities and networking of economic agents. As our estimates show, market-generated flows are much more information intensive than non-market flows.[29]

Nevertheless, our results show that disembodied knowledge, generated via patent trade and citation flows, are less geographically restricted and, therefore, their effective reach is beyond that of knowledge embodied in goods and inventors, as the latter channels involve movements of goods and people, respectively. The generation mechanism of knowledge diffusion plays important role. We find that non-market channel knowledge spillovers (citation flows) are more far-reached than market-based flows, with knowledge flows via inventors' mobility to be the most geographically confined among the market-based flows. Specifically, ideas based on citation flows are 10 (or 4 based on traded patent flows) times less restricted by a state border than knowledge flows based on inventors' migration and 2.5 (or equal to, based on traded patent flows) times less restricted than knowledge flows based on trade of goods. In addition, the geographic scope of knowledge based on citation flows is about 13 (or 5 based on traded patent flows) times larger than knowledge flows based on inventors' mobility and 10 (or 4 based on traded patent flows) times bigger to knowledge flows based on trade of goods.

To get a better sense of the size of our coefficients, we compare our findings with prior evidence reported in the literature. A study which is conceptually close to ours is that of Mowery and Ziedonis (2001). In their analysis of university-generated knowledge flows, Mowery and Ziedonis (2001) find that geographic distance matters more for the channel of market of contracts (patent licenses) to non-market channels (citations) and the geographic stretch of the latter is about 3 times bigger than that of the former; a relationship which also finds support by our estimates. Contrary to some arguments expressed in the literature (Audretsch and Stephan, 1996, p.651), we also concur that geographic proximity is more essential to the operation of market contracts compared to the operation of informal, non-market flows based on citation flows.[30]

Another study that discusses estimates from two different channels of knowledge flows is the study of Peri (2005), which consists the first attempt in the literature to perform a comparison between disembodied knowledge flows (citations) and embodied knowledge in trade of goods. However, rather than jointly estimating the effect of geography on citation and trade flows, Peri (2005, p.317) borrows distance and border trade estimates from the studies of Anderson and Van Wincoop (2003) and Feenstra (2003) to conclude that border and distance reduce physical trade 4 to 5 times more than they reduce citation flows. By jointly estimating the effect of geographic characteristics on different channels of knowledge flows, we find that on crossing a state border, knowledge based on citation flows is about 2 to 3 times larger than knowledge based on trade flows. In addition, the geographic stretch of citation flows is 10 times larger than that of trade flows. Our distance effects are bigger compared to those reported in Peri (2005), but reasonable, if one considers that we investigate flows within a country and not across word regions as the aforementioned study does.

We further compare our findings with other strands of research that have analyzed knowledge flows. We first turn our attention to the patent-citation literature. Although cross-study comparisons are not

[29]Such social proximities have been identified in the literature (Saxenian, 1994) as important factors for knowledge exchange. For example, Breschi and Lissoni (2009) apply a social network analysis to derive maps of social connectedness among patent inventors. The authors find that the probability to observe a citation is positively influenced by social proximity of the inventors.

[30]Audretsch and Stephan (1996) studied interactions between university-based scientists and biotechnology firms based on disclosures in firms' initial public offering documents about academic researchers' roles in the firms.

always easy due to different measures of distance, omissions of border, and different level of analyses employed, we can still recover some effects that can be compared with ours. Note that we can only compare our citation estimates with those reported in the patent-citation literature. We begin with the seminal study of Jaffe et al. (1993), which reports a drop of 50% to 60% in the citation flows when they transcend a state's border in the US. Based on our citation estimates, the drop on learning when crossing a state border ranges from 73% to 76%. Our estimates are also not widely different from those documented in studies which examine knowledge flows across world's regions. Maurseth and Verspagen (2002), for example, use citations between European-granted patents across 122 European regions and find that the effect of distance ranges from -29% to -38%, while the border effect varies from 53% to 56%. Peri (2005) examines knowledge flows across 144 regions from different countries of the world and reports a reduction of 21% when knowledge flows cross a region border and a 3% drop for each 1,000 km traveled. We find a reduction of about 24% on crossing a state border and a 0.5% drop for every 500 miles traveled within the US.

Finally, the localization robustness of weightless ideas documented in our study, corroborates with findings from less related strands of research. For example, studies in the financial trade literature, using 'gravity-like' models, examine whether geographic distance imposes a hurdle on financial asset transactions, which are, compared to goods, weightless. In fact, Portes et al. (2001) and Portes and Rey (2005) examine the determinants of cross-border assets (corporate bonds equities and treasury bonds) and show that geographic distance reduces financial asset trade approximately up to 80%.

From the exposition of related evidence from various strands of literature, it is reassuring to conclude that that size of our system estimates is comparable to prior studies and reasonable. Our estimates show, from different angles, the relative importance of proximity across all channels in a rather reasonable and coherent way. The evidence provided in the literature from a single channel of knowledge flows (for instance, patent citations) is enforced in our study by the joint evidence of other channels.

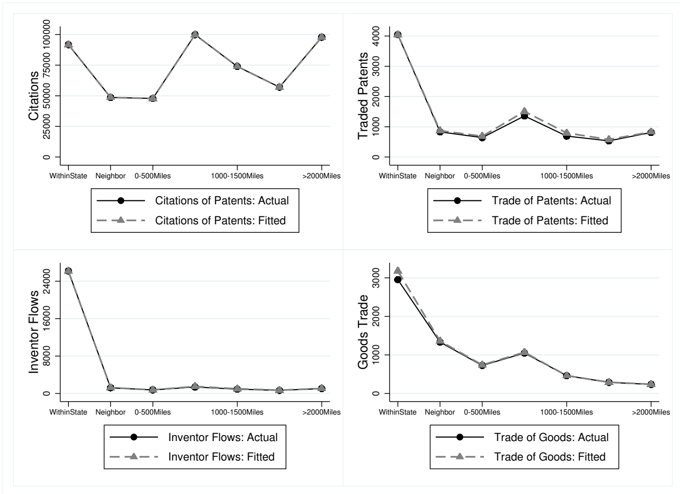
Concerns, however, expressed in the literature for potential caveats in each channel proxing knowledge flows still pertain in the present study. For example, the origin of citations, i.e., whether they are added by inventors or examiners on the patent document may have different implications for the geographic stretch of citation flows. A more proper treatment of citation flows and, consequently, of their geographic stretch, it would require the distinction into inventor- versus examiner-origin citations. The USPTO has allowed such distinguish only very recently, since 2001 (Alcacer and Gittelman, 2006; Thompson, 2006).[31] Performing such analysis, however, considerably restricts the data set and scope of this paper and, therefore, is left for future investigation. Patent trades, as a vehicle of knowledge flows, is not without flaws either. The reason is that patent transactions do not always relate to technological acquisition, but they could also serve strategic purposes. Consequently, this channel is a rough proxy of knowledge diffusion as it contains some 'noise', too. Unfolding, however, the reason behind the patent transaction, and consequently the extent of technological knowledge patent trades carry has not been easy so far, as it requires information across different databases (e.g., citations a patent receives from the perspective buyer before the transaction - firms that acquire a patent could also previously cite the patent - and the size of a firm, as small-sized firms tend to buy patents for technology purposes, while large ones for strategic reasons), which are not matched yet, or survey data that are not available. Licenses of patents, instead of patent trades, could alleviate some worries as licensing involves more contacts and potential knowledge exchange between the seller and buyer, but such data are generally proprietary. Further, instead of using inventors' job moves, one could use a more refine measure such as informal meetings and exchange of ideas of inventors during the inventive process (or probability to enter into local/international networks of research based on inventors' characteristics during the inventive process) as the study of Giuri and Mariani (2013) does. The latter, relies on survey data by interviewing european patent inventors about interactions that were important for the development of a patent. Such data, although very useful, is not yet available for the US. Lastly, disaggregation of imports into different categories (e.g., technological capital goods) would be a more

[31] A study by Criscuolo and Verspagen (2008) examines patents from the European Patent Office (EPO) and exploits such distinction the EPO provides about the source of patent citations since 1979. The authors find that inventor-origin citations are more geographically localised than their examiner-origin counterparts as inventors tend to choose their citations from within a narrower geographical space than examiners do.

insightful proxy of knowledge flows that operate via trade. Instead, we relied on value of state's total imports as it is the only available piece of information at the state level.

At this point, we can visualize some of our results with the use of a graph. Figure 2 below depicts the estimated (dashed line) along with the actual values (bold line) of geographic resistance factors on all four types of knowledge flows. Specifically, it shows the actual and estimated decay of knowledge flows moving out of a state, nearby area (about 500 miles), and out by steps of 500 miles.

Figure 2: Decay of Knowledge Flows Due to Geographical Barriers



The graphical evidence confirms the significant drop in knowledge flows when they transcend a state border. Distance further decreases their mobility. The geographic reach of non-market knowledge spillovers, based on citations, is far more stretched in space than any other type of flow. Followed by traded patent flows, disembodied knowledge flows are less geographically confined in space compared to embodied knowledge in goods and patent inventor flows. The latter, exhibit the sharpest decay. All flows shoot up for geographic distances between 500 and 1,000 miles due to interactions of a typical state with Illinois, Texas, and Michigan, which are located in the middle of the country and are among the most innovative states of the US. The "California effect" is pronounced for idea flows, slightly apparent for inventor flows and completely absent for trade of goods. Finally, we can also appreciate from the figure that actual and estimated values are very close to each other indicating a good fit of our model.

Robustness

We have performed several checks to sharp the robustness of our results. We examined whether the geographic scope of flows from top innovator states differs (e.g., is wider) from the 'average' state flows. Relevant ideas are generated only by few institutions in states closer at the frontier of technological development, while other states are receivers of these ideas and apply adjustments to them. To explore this aspect, we re-estimate the tri-variate and four-variate SUR systems considering knowledge flows originating only from the top innovator states.[32] Table A.2 in the Appendix presents the results for the top 10

[32]We select the top innovators to be the states with high total R&D spending which, combined, accounts for approximately 70% of the total US R&D activity in our sample. Accordingly, the states of California (CA), Massachusetts (MA), Michigan (MI), New Jersey (NJ), New York (NY), Texas (TX), Illinois (IL), Pennsylvania (PA), Maryland (MD), Washington (WA), and Ohio (OH) may act as innovation leaders.

innovator states. Our results confirm the broader reach of leaders' flows only for two out of four channels. Specifically, estimates show that top leaders' knowledge flows based, on citations and trade flows, are approximately 1.5 and 1.2, respectively, less geographic localized, both in terms of state border and distance, than average state flows, while for the rest of the channels the geographic scope of the leaders' flows is similar to the average state flows. As before, similarities in technological effort and technological specialization still play an important role. The analysis of leaders' flows confirms that regardless of the origin, i.e., whether flows come from an average or innovator state, citation flows exhibit the largest spatial mobility.

We proceeded with further robustness analysis, which is briefly described here and available upon request. To control for outliers, we excluded California, which is a top performer in terms of innovation.[33] Results mildly changed, but overall conclusions drawn from Table 2 still hold. A notable change is that the very long distance (larger than 2,000 miles) effect disappears due to the drop of California.

We split our sample in two sub-periods and estimate knowledge flows for the periods, 1993-1999 and 2000-2006, in order to examine whether the importance of proximity, either geographic or technological, has changed over time. Unlike the geographic distance effect, which remains virtually unaltered for all types of flows, technological distance appeared to matter slightly more, over time and only for traded patent flows. Geographic distance may still matter, if face-to-face interaction is important, even in high-tech sectors, as knowledge is tacit and hard to codify (Evans and Harrigan, 2005; Peri, 2005; Disdier and Head, 2008).

We also split the sample by the importance of patented inventions. We define 'valuable' patented invention a patent that receives 50 or more citations and divide our patents into *high-cited* and *low-cited* patents. The former group, accounts for 4% of the total patents.[34] We replaced *Patent Flows* with low- and high-cited patents instead, and re-estimated the tri-variate and four-variate SUR systems, each one for high- and low-cited patents. Results did not not alter significantly. The only notable difference is that high-cited patents, as expected, are slightly less geographically restricted than low-cited ones.

We, further, classified patent citations into citations of traded patents and citations of non-traded patents, and replicate the analysis. All previously drawn conclusions hold. Additionally, the citations of the former are found to be more geographically bounded than those of the latter. Even within the same channel such as citation flows, there is some differentiation in the spatial reach.

Moreover, we tried to jointly estimate knowledge flows at a finer disaggregation level, for example, for six technological sectors, namely commuters, electronics, chemicals, drugs, mechanical and others. Data limitations allowed us to explore only two channels, traded patents and citation flows, out of four. Sector level estimates were not that different from state-level estimates and there was little variation across sectors. Localization of knowledge was evident in all sectors, with computer and electronic sectors to slightly exhibit the most extensive geographic diffusion of knowledge, whereas, chemical and drugs the least.

Finally, we employed alternative definitions of traded patent flows, for example, 'first flow' and 'last flow', as defined in the Data section, instead of (all) traded patent flows and re-produce the same analysis. Results remain robust.

Ideally, we would also like to consider foreign direct invest (FDI) flows as an additional channel of (disembodied) knowledge. Lack of state level data, prevented us from doing so.

Overall, results do not change in any significant way across different specifications, sub-samples and alternative definitions.

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[33]See Table A.1 in the Appendix for states' statistics.

[34]We choose the 50-citation threshold in order to have a clear split between valuable and less valuable patented inventions. According to the statistics, highly cited patented inventions in our sample amount to approximately 5,000 patents and receive 949,000 citations, while low-cited to 120,000 patents and receive 26,000 citations.

4.2. Does Available Knowledge Contribute to Local Innovation Production?

We have established that knowledge flows across states depend on the geographic and technological proximity of the states. The existence of these flows, however, does not necessarily support existence of externalities of knowledge on local (state) innovation. Available knowledge originating in other states may bring, along with new ideas, a reduction in innovation possibilities, thus generating a zero or even negative net effect on the productivity of researchers in innovation. Consequently, no clear prior exists on the sign and magnitude of innovation elasticities.

Therefore, the second task of this paper is to assess the effect of external available knowledge on states' innovation activity. In doing so, we estimate a function of innovation production, as described in equation (3), and assess the individual effect of each channel of knowledge flows on local production of innovation.

The dependent variable of equation (3) is the innovation output Q, which is the log of number of patents granted to a state in year t weighted by patent citations, taking into account the grant year and the technology field of the patent.[35] We estimate equation (3) with OLS controlling for time effects.

Table 3 reports estimated elasticities of state's own R&D stock and external accessible to a state flow-weighted R&D stock gained via the four channels. Column (i) shows innovation elasticities of all states, when the weights, f_{ij}, in equation (3) are standardized by actual (raw) flows, F_{ij}, and column (ii) when fitted values, $\hat{F}_{ij}$ are used for the standarisation. Columns (iii) and (iv) report innovation elasticities, in similar fashion, but when external accessible flow-weighted R&D stock originates only from the top 10 innovator states in the US. In fact, the last two columns include the top 10 states in the regressions only as senders of knowledge flows and the remaining states as receivers. Consequently, A^{α}_{ij} in equation (3) is defined as A^{α}_{ij}=$\sum_{j \in Top\,10}(f_{ij}A_{ij})$. This allows us to minimize potential endogeneity in estimating the coefficient μ of A^{α}_{ij}.

As Table 3 shows that estimates of actual flows reported in column (i) and fitted flows in column (ii) are very close to each other. Similar evidence emerges from columns (iii) and (iv). This alleviates concerns that our results rely too much on the modeling of the knowledge flows and, therefore, are susceptible to model criticism. Using a more direct measure, that of raw flows, we find similar estimates. Furthermore, despite of the potential worsening of the endogeneity problem when external accessible R&D stock originates from all states, estimates are overall quite close across different specifications.

More specifically, results strongly support that state's own ($lnR\&D_{own}$) as well as external accessible R&D stocks are significant contributors to states' innovation production. We find that a one percent increase of state's own R&D is associated with an increase in the local production of innovation by 0.40% (column i) to 0.44% (column ii). This effect drops by half, when top innovator states are the only source of relevant knowledge flows. Apparently, only a number of states - the most innovative ones - invest heavily on home-produced technological knowledge. The majority of the states appear to produce innovation by relying more on external accessible rather than on homegrown knowledge. The latter, contributes from 19% (column iii) to 22% (column iv).

[35]More specifically, every patent is assigned to an issue year and technology field. We have 14 years and 37 technology groups; therefore, every 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 the following one: $w_1 = 0.1$, if citation belongs to the first, $w_2 = 0.2$ for the second, $w_3 = 0.3$ for the third, and $w_4 = 0.4$ for the fourth quantile. We then sum these values up for every state and for every year t and calculate our weighted measure of innovation output.

Table 3: Elasticities of Innovation Production Function

	Flows from All States[a]		*Flows from Top 10 States*[b]	
	Actual	Fitted	Actual	Fitted
	(i)	(ii)	(iii)	(iv)
$lnR\&D_{own}$	0.40***	0.44***	0.19*	0.22**
	(0.091)	(0.087)	(0.109)	(0.111)
$lnR\&D_{citations}$	0.42***	0.43***	0.50***	0.49***
	(0.104)	(0.104)	(0.102)	(0.105)
$lnR\&D_{patents}$	0.11**	0.15***	0.11**	0.12**
	(0.048)	(0.049)	(0.048)	(0.046)
$lnR\&D_{inventors}$	0.03	-0.00001	0.09	0.09
	(0.087)	(0.085)	(0.086)	(0.083)
$lnR\&D_{trade}$	0.16	0.12	0.17**	0.15*
	(0.114)	(0.098)	(0.087)	(0.083)
Constant	1.46***	1.33***	1.73***	1.71***
	(0.362)	(0.330)	(0.294)	(0.303)
Observations	134	134	97	97
R^2	0.87	0.88	0.81	0.81

All regressions include time dummies. All variables are in logs. Standard errors reported in parentheses; Coefficients of *Constant* term are omitted; $lnR\&D_{own}$ is state's own R&D stock; $lnR\&D_{citations}$, $lnR\&D_{patents}$, $lnR\&D_{inventors}$, and $lnR\&D_{trade}$ are external available to a state citation-, patent-, inventor-, and trade-weighted external R&D stocks, respectively; (***), (**), and (*): significance at 1%, 5%, and 10% level, respectively.

[a] All states were included as senders (origin) of knowledge flows. All states were included as receivers (destination) of knowledge flows.

[b] Only the top 10 innovators were included as senders (origin) of knowledge flows. Only the remaining 38 states were included as receivers (destination) of knowledge flows. 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).

Other states' R&D effort has also a positive and statistically significant effect on local production of patents and, in some cases, is greater then state's own R&D effect. This is particularly true for specifications (iii) and (iv). The non-market channel of citation flows is the channel that largely shapes local innovation production, as a one percent increase of external accessible citation-weighted R&D ($lnR\&D_{citations}$) is associated with an increases in the production of innovation from 0.42% (column i) up to 0.50% (column iii). The combined effect of the market-based channels is about half of that of citation flows. A one percent increase of external accessible traded patent-weighted R&D ($lnR\&D_{patents}$) relates to 0.11% (column i) to 0.15% (column ii) increase in state's innovation. Similarly, a one percent increase of trade-weighted available R&D stock ($lnR\&D_{trade}$) enhances patent production by 0.12% (column ii) to 0.17% (column iii); however, the effect is not always statistical significant. Finally, a mixed picture emerges for external inventor-weighted R&D ($lnR\&D_{inventors}$), which is negatively associated with state's innovation production, when all states flows are considered, and positively, for flows that originate only from the top innovator states. However, in both cases, estimates are statistically insignificant and close to zero.

Summing up, we find that knowledge flows are relevant to local innovation production as external accessible R&D, gained through different channels, has a strong positive effect on a state's innovation activity and the effect is as large, for some cases, as state's homegrown R&D stock. Second, the effective reach of disembodied knowledge, exemplified by citations and patent trades, is larger than that of embodied knowledge in goods and inventors. Such finding corroborates with theoretical studies of endogenous growth (Grossman and Helpman, 1991; Rivera-Batiz and Romer, 1991), which have emphasized the important consequences of disembodied knowledge flows for technology transfer and economic growth, but have not offered any empirical documentation. Lastly, external available flows that operate via market mechanisms have smaller effect on local patent production compared to non-market generated flows. This finding is in line with conclusions drawn in previous section, where formal, market-based flows are found to be less far-reached in space compared to informal, non-market flows, as the former require movements of goods, inventors, or some degree of geographic proximity between the seller and the buyer of a good or patent.

As a further check, we run all regressions in Table 3 lagging all variables on the right-hand side by one period to overcome potential immediate feedback effect. Results did not change in any significant way.

Overall, our estimates of own R&D elasticity for all states (40%-44%) are in the vicinity of estimates reported in the international spillover literature, and in particular in the studies of Peri (2005) (60%-80%), Branstetter (2001) (72%), Pakes and Griliches (1980) (61%), Bottazzi and Peri (2007) (78%), and in several other studies. Similarly, our estimates of external accessible R&D gained mainly through citations (42%-50%) are close to what the literature reports, Peri (2005) (40%-50%) and Bottazzi and Peri (2007) (55%).

5. Conclusion

This paper offers novel insights in knowledge diffusion across states of the US and its consequences for local innovation activity. We use a simple, common framework to jointly analyze and learn more about the relative mobility of four different channels of knowledge flows that operate via (i) citations of patents, (ii) traded patents, (iii) inventors' mobility, and (iv) trade of goods. Thus far, these flows been studied separately from different avenues in the literature. To jointly evaluate these flows, we develop novel econometric techniques appropriate to the nature of the data. In a second stage, we assess the individual effect of these jointly estimated flows on local production of innovation.

Using newly developed data for the states of the US, our findings support that geographic proximity, in terms of distance and contiguity, matters for the spread of knowledge, as it has been massively documented in the literature. Our findings further confirm that disembodied knowledge is less geographically restricted and, therefore, its effective reach is beyond that of knowledge embodied in trade or inventors, as the latter involve movements of goods and people, respectively. Furthermore, non-market channel knowledge flows are more far-reached than market-based flows, with inventors' mobility flows to be the most geographically confined. Finally, with respect to other types of closeness, technological effort proximity of states and technological production structure similarities greatly enhance knowledge interactions across states.

The implications of our findings for the literature are potentially relevant. Although theoretical trade-growth studies (Grossman and Helpman, 1991; Rivera-Batiz and Romer, 1991) emphasize the important consequences of disembodied knowledge flows for technology transfer and economic growth, there has been little effort, on the empirical side, to thoroughly explore this issue. Along with other important studies, this paper makes an effort toward this direction and empirically confirms the important geographic scope of disembodied knowledge flows. Knowledge, especially disembodied, is significantly relevant to local innovation production, as external accessible R&D gained through citation and traded patent flows has a strong positive effect on a state's innovation activity as large as that of state's own R&D stock.

An issue deserving further inquiry is the role of another type of proximity, that of social proximity, on state-level localization of knowledge diffusion. Learning more about the causes of home bias is needed before an assessment of welfare consequences can be undertaken.

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Appendix

Table A.1: Summary Statistics per State

State	Traded Patents		Citations		Inventors' Mobility		Traded Goods		Scientists		R&D spending	
	mean	Std.	mean	Std.	mean	Std.	mean	Std.	mean	Std.	mean	Std.
AL	120.21	50.39	2,698.21	1,708.61	151.43	81.19	136,742.80	14,813.17	7.11	1.19	2.15	0.33
AR	37.21	19.01	1,444.86	877.01	59.07	36.61	102,072.50	4,198.25	3.13	0.43	0.40	0.06
AZ	195.36	73.67	8,837.00	5,110.42	572.21	319.18	106,381.90	15,401.81	7.74	1.20	3.07	1.05
CA	3,295.79	1,395.30	196,683.50	128,920.90	7,808.07	4,499.69	609,102.80	63,047.66	84.56	10.10	48.14	7.72
CO	388.50	147.68	14,088.14	8,643.05	813.14	443.91	94,217.51	9,185.09	13.12	1.66	4.14	0.78
CT	439.50	101.38	23,682.86	13,361.11	855.00	428.61	110,648.00	5,636.09	10.26	1.15	5.12	1.68
DE	616.93	236.85	18,913.21	10,836.44	214.07	118.12	32,635.48	2,642.04	3.92	0.44	1.50	0.40
FL	537.21	186.50	24,397.36	15,597.80	938.29	471.25	240,354.50	21,688.26	17.48	2.12	4.81	0.61
GA	279.71	117.16	10,802.79	6,667.95	561.71	304.58	311,019.70	5,926.84	12.18	1.71	2.81	0.73
IA	118.14	64.38	4,088.86	2,351.09	236.29	129.34	124,773.90	16,114.45	4.92	0.29	1.22	0.21
ID	120.00	162.19	14,418.21	10,980.25	251.14	129.99	28,709.28	3,891.09	2.50	0.36	1.01	0.31
IL	843.00	259.04	49,023.36	27,972.70	1,486.86	755.91	477,459.10	28,034.33	23.69	1.45	9.70	1.56
IN	230.36	65.77	10,971.21	6,294.65	596.36	341.86	295,413.40	48,487.71	9.66	0.85	3.61	0.78
KS	84.50	38.41	2,948.93	1,790.36	145.50	74.67	108,231.60	8,599.44	4.31	0.37	1.40	0.58
KY	56.43	23.31	3,515.93	2,554.01	158.57	84.85	188,553.80	40,155.48	4.91	0.52	0.81	0.23
LA	84.43	31.58	3,182.07	1,715.27	153.00	80.46	128,699.20	12,328.39	5.94	0.23	0.66	0.16
MA	864.86	324.21	44,793.21	27,329.66	2,093.86	1,162.75	183,286.00	9,336.05	29.14	3.81	13.11	2.07
MD	269.64	111.28	10,664.07	6,672.65	753.07	421.15	145,223.30	17,471.29	25.26	3.30	9.26	1.88
ME	27.14	23.28	1,133.64	771.53	54.21	29.92	31,311.10	4,395.33	2.46	0.13	0.28	0.11
MI	730.79	413.72	32,637.21	19,022.82	1,475.93	785.10	364,852.50	45,548.45	17.65	1.54	15.26	2.35
MN	592.79	267.34	38,575.50	25,748.62	1,041.79	603.92	164,072.20	20,179.74	11.42	1.36	4.40	1.06
MO	217.36	64.73	8,520.64	4,745.15	445.00	247.34	218,572.90	15,572.51	9.80	0.53	2.43	0.41
MS	50.00	31.41	1,320.50	1,092.70	59.57	30.82	89,770.17	10,231.12	3.38	0.23	0.55	0.28
MT	24.07	13.76	1,092.57	788.20	40.64	22.70	16,141.39	1,686.00	1.98	0.19	0.18	0.06
NC	280.21	117.20	12,178.07	7,484.07	778.64	432.56	280,150.30	21,377.07	17.31	2.47	4.79	1.23
ND	16.50	9.10	409.79	222.38	22.07	12.38	18,522.55	3,788.67	1.63	0.46	0.20	0.12
NE	67.00	28.11	1,803.93	1,029.49	69.50	34.96	65,771.58	7,101.39	2.97	0.11	0.48	0.16
NH	126.21	96.43	4,717.07	3,065.47	313.86	171.22	38,112.65	7,528.93	2.66	0.36	1.11	0.46
NJ	824.36	359.10	47,549.36	28,250.40	1,930.14	1,082.08	340,518.00	6,643.18	23.38	1.92	11.59	1.18
NM	81.43	134.75	2,547.21	1,697.45	180.29	98.31	28,924.74	1,935.51	8.44	0.79	3.75	0.74
NV	230.50	231.23	5,551.64	4,078.32	114.64	67.09	47,653.47	9,687.69	2.11	0.33	0.46	0.14
NY	1,106.86	630.08	81,310.00	49,068.60	2,162.43	1,115.42	400,433.90	17,918.45	45.88	2.40	12.86	0.89
OH	625.64	196.06	31,767.50	18,167.59	1,372.29	718.46	463,485.00	57,176.91	21.68	1.76	7.39	0.65
OK	91.21	40.04	4,933.93	2,583.87	190.21	90.30	88,464.96	8,744.00	4.96	0.24	0.67	0.10
OR	174.93	78.53	8,521.36	5,138.81	469.64	252.54	98,741.59	15,711.60	8.12	1.13	2.14	1.00
PA	685.57	175.40	28,777.71	16,437.27	1,578.14	848.62	387,158.10	33,121.79	28.08	2.48	9.58	0.92
RI	72.57	32.57	2,199.57	1,282.51	149.14	78.35	25,858.19	2,106.39	2.87	0.32	1.35	0.48
SC	82.86	45.09	4,171.50	2,422.89	234.07	113.53	150,595.30	20,641.18	5.50	0.48	1.22	0.37
SD	8.57	6.80	560.79	370.08	14.86	9.73	19,459.47	3,205.89	1.14	0.06	0.09	0.04
TN	186.71	58.57	6,514.93	4,057.05	363.43	186.72	274,214.60	60,689.53	9.61	0.69	2.18	0.57
TX	842.07	234.75	56,455.14	35,821.14	2,164.93	1,225.83	494,561.20	51,263.84	34.72	3.51	11.39	2.42
UT	159.64	95.54	7,832.50	5,084.13	317.07	167.58	56,557.52	8,069.14	5.33	0.45	1.34	0.29
VA	359.79	70.78	12,316.00	7,838.49	488.71	253.71	193,182.50	9,789.51	19.47	2.85	5.35	1.60
VT	19.21	11.49	816.86	495.21	116.93	58.96	19,019.74	4,182.37	1.91	0.20	0.39	0.08
WA	348.86	167.55	20,755.07	13,582.13	788.36	436.76	137,307.80	15,197.25	15.55	2.21	8.67	2.01
WI	273.21	76.57	17,289.79	11,354.52	740.79	374.79	215,328.20	27,417.95	9.23	0.87	2.77	0.54
WV	15.79	13.00	605.29	369.56	55.64	29.29	51,474.45	1,367.96	2.28	0.19	0.44	0.07
WY	13.21	7.21	379.00	251.87	21.14	12.70	11,545.84	1,760.98	0.89	0.09	0.08	0.02

State's two-letter abbreviation reported in first column; *Traded Patents*, *Citations*, and *Inventors' Mobility* are occurrences (non-negative integers); *Traded Goods* are in millions of constant (2000) US dollars; *Scientists* (science, engineering, and health researchers) are in thousands; and *R&D spending* in millions of constant (2000) US dollars.

Table A.2: Determinants of Knowledge Flows in the US (Top Innovator States)

	Tri-variate SUR Estimates[(I)]			**Four-variate SUR Estimates**[(II)]			
	Citation flow[a]	*Patent flow*[b]	*Inventor flow*[c]	*Citation flow*[a]	*Patent flow*[b]	*Inventor flow*[c]	*Trade flow*[d]
		(i)			(ii)		
State Border	-0.67	-2.42	-3.53	-0.54***	-2.34***	-3.55***	-1.27***
	(0.001)	(0.001)	(0.010)	(0.001)	(0.013)	(0.016)	(0.016)
Nearby States [500 *miles*]	-0.87	-2.90	-4.11	-0.75***	-2.85***	-4.10***	-2.31***
	(0.001)	(0.001)	(0.010)	(0.001)	(0.016)	(0.027)	(0.027)
Distance $[500 - 1,000\,miles]$	-0.91	-2.99	-4.32	-0.75***	-2.82***	-4.31***	-2.89***
	(0.001)	(0.001)	(0.010)	(0.001)	(0.010)	(0.017)	(0.017)
Distance $[1,000 - 1,500\,miles]$	-0.96	-3.09	-4.42	-0.78***	-2.95***	-4.43***	-3.36***
	(0.001)	(0.001)	(0.010)	(0.001)	(0.019)	(0.014)	(0.014)
Distance $[1,500 - 2,000\,miles]$	-1.05	-3.10	-4.50	-0.88***	-3.00***	-4.54***	-3.62***
	(0.001)	(0.002)	(0.011)	(0.001)	(0.016)	(0.021)	(0.021)
Distance $[2,000 - 2,500\,miles]$	-0.74	-3.10	-4.49	-0.64***	-2.94***	-4.45***	-3.73***
	(0.001)	(0.001)	(0.012)	(0.001)	(0.010)	(0.012)	(0.012)
TechnologicalDistance	0.01	-0.03	-0.20	0.09***	-0.05***	0.09***	-0.10***
	(0.001)	(0.001)	(0.011)	(0.001)	(0.016)	(0.019)	(0.019)
StructuralCloseness	0.63	0.53	-0.34	1.28***	0.77***	0.44***	-0.10***
	(0.001)	(0.010)	(0.030)	(0.001)	(0.042)	(0.053)	(0.053)
Observations	6,720	6,720	6,720	1,341	1,341	1,341	1,341

All regressions include time dummies and origin and destination state fixed effects. Standard errors are reported in parentheses (heteroskedastic robust standard errors only for the single equation estimates); Coefficients of *Constant* term are omitted; *State Border* takes the value of 1 for flows exchanged between neighbor states (share a common border) i and j and 0 otherwise; *Nearby States* [500 *miles*] takes the value of 1 for flows exchanged between states that do not share a common border and their geographical centers are located within a distance of 500 miles, and 0 otherwise; *Distance* $[500 - 1,000\,miles]$, *Distance* $[1,000 - 1,500\,miles]$, *Distance* $[1,500 - 2,000\,miles]$, and *Distance* $[2,000 - 2,500\,miles]$ are distance classes of 500 miles each and take the value of 1 for flows exchanged between states i and j that are located within 500 to 1,000, 1,000-1,500, 1,500-2,000, and 2,000-2,500 miles, respectively, and 0 otherwise; *TechnologicalDistance* is the degree of proximity of the technological effort (*R&D/Scientists*) of states i and j; *StructuralCloseness* is the degree of technological similarity of technological specialization in production sectors of states i and j; (***): significance at 1% level.

[I] : Specification (I) reports negative binomial estimates of tri-variate SUR (column i).

[II] : Specification (II) reports estimates of four-variate mix count and continuous SUR (column ii) for the years 1993, 1997, and 2002.

[a] *CitationFlows* are citation flows originating from the top 10 most innovative states (all states are included as receivers).

[b] *PatentFlows* are traded patent flows originating from the top 10 most innovative states (all states are included as receivers).

[c] *InventorFlows* are inventor flows originating from the top 10 most innovative states (all states are included as receivers).

[d] *TradeFlows* are trade (imports) of goods flows originating from the top 10 most innovative states (all states are included as receivers) .

Top 10 most innovative states are: California (CA), Massachusetts (MA), Michigan (MI), New Jersey (NJ), New York (NY), Texas (TX), Illinois (IL), Pennsylvania (PA), Maryland (MD), Washington (WA), and Ohio (OH).