Beyond Borders: The Influence of Social Networks and Labor Flows on Innovation Spillovers *

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Abstract

We provide novel evidence that knowledge spillovers are less geographically confined than prior research suggests. Social ties and labor flows play important roles in facilitating distant knowledge flows. At the individual patent level, pairwise citations rise significantly when social ties and job flow probability increase. At the firm level, the innovation activities of social ties and job flow-based peers strongly predict future innovation in focal firms, with elasticities of 0.124 and 0.118, respectively. These effects are stronger for disruptive and pioneering technologies, and for counties with greater economic connectedness, more educated populations, wealthier residents, and more tech workers. These spillover effects disappear following state court decisions strengthening non-compete clause enforceability. We confirm that our findings are causal using state tax credit variations as instruments. The findings provide important implications for local policies aimed at fostering innovation and economic growth.

JEL classification: O31, O33, J61, J62, R11, K31

Keywords: social network, innovation, knowledge spillovers, labor flow, non-compete clause

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1 Introduction

Knowledge spillovers are crucial for stimulating innovation and driving economic growth. This has sparked extensive research aimed at understanding their facilitating mechanisms. The literature has traditionally emphasized spatial factors, demonstrating that knowledge spillovers are highly localized and decay rapidly with physical distance (e.g., Jaffe et al. 1993, Audretsch and Feldman 2004, Catalini 2018, Atkin et al. 2022, Roche et al. 2024). This provides a compelling rationale for agglomeration and technology clusters.

However, emerging evidence suggests that geographic proximity may not be the sole determinant of knowledge diffusion. Using aggregated and anonymized county-pair friendship links from Facebook, Bailey et al. (2018) develops a Social Connectedness Index (SCI) to measure social ties between counties.[1] They find that social connectedness strongly correlates with patent citations and migration flows between counties, even after controlling for geographical distance. They further suggest that exploring potential causal relationships behind these correlations could provide insights into the mechanisms shaping knowledge spillover, innovation, and ultimately economic growth.

Motivated by Bailey et al. (2018), we hypothesize that social networks and migration of people act as conduits for the diffusion of ideas and innovation that transcend geographic boundaries. Our conceptual framework posits the following: strong social ties or higher labor flows between firms' R&D locations can enhance information exchange and the flow of ideas over long distances. As a result, an increase in innovation by distant peer firms with strong social connectedness or labor flow can foster innovation activities by a focal firm.

We examine the hypothesis empirically and provide causal evidence—at both the individual patent level and the firm level—on the role of social networks and labor flows in enabling knowledge spillovers beyond geographic constraints. We also examine state-level policies on

[1] Facebook's immense scale, broad market penetration, and widespread popularity make the SCI a valuable proxy for online social networks and real-world connections between U.S. counties (Bailey et al. 2018, 2019, 2020, 2022, Kuchler et al. 2021, Rehbein et al. 2020).

non-compete clause enforceability and heterogeneities in regional socioeconomic variations to provide insights for policymaking.

We consider U.S. publicly listed firms operating in the same three-digit SIC code as peers to each other and geo-code a firm's R&D location by its lead inventor' address. We construct two key peer innovation measures. The first one is social-ties-weighted peer innovation, $SocialPeer_Pat$, where the strength of social tie between two counties is measured by the SCI (Bailey et al. 2018). This measure places more weight on peer inventors who share strong social ties with the focal firm. We exclude peers who share R&D locations with the focal firm to ensure that we are capturing distant knowledge flows.

The second one is labor-flows-weighted peer innovation, $LaborFlowPeer_Pat$. We use workers' job-to-job transition probability across industries and states to weigh peer innovation. The job-to-job flow data come from the U.S. Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) database (Hyatt et al. 2014, Hahn et al. 2017) and capture worker flows across jobs and states. This measure then places greater weight on peer inventors who reside in regions sharing higher labor flows with the focal firm.

We first provide a micro foundation for the effects of social ties and job flows on knowledge spillovers. We test whether pairwise patent citations from a focal firm's R&D lab to its out-of-state peers can be explained by social connectedness and job flows. We find that increases in social ties and job flows are positively associated with an increase in pairwise citations. The effects remain strong even after controlling for geographical proximity and other channels of peer effects.

We then consider an important state-level policy, the enforceability of non-compete clause (NCCs), and investigate its role in influencing knowledge spillovers and innovation. We find that the gains in knowledge spillovers from social interaction and job flows are almost entirely erased following court rulings in favor of stronger NCC enforceability. Furthermore, the weakening of both job flows and social ties suggests that these channels are complementary. Labor flows help maintain and strengthen social networks, and when labor mobility is

restricted, social networks become less effective in facilitating knowledge diffusion. Thus, our analysis suggests an adverse impact of stronger NCC enforceability on innovation spillovers and provides insight into the potential underlying mechanisms.

Next, we focus on the diffusion of disruptive technologies—fundamental breakthroughs that serve as catalysts for subsequent waves of innovation. Following the framework of Kalyani et al. (2023), we identify two key categories of patents: disruptive technology patents and pioneer patents within disruptive fields, which account for 25.3% and 17% of our sample, respectively.

We find that social networks and labor flows are especially useful in facilitating knowledge spillovers for these high-impact technologies. The effect of job flow, in particular, is five times greater for disruptive and pioneering technologies compared to the average. In contrast, for non-disruptive and non-pioneering technologies, the influence of labor flows is negligible and statistically insignificant. This suggests that the average effect of job flow is entirely driven by its influence on the diffusion of disruptive and pioneering innovations. Similarly, the impact of social ties is 1.5 to 1.9 times greater for these transformative technologies. By enabling the flow of tacit knowledge and expertise, these social and professional networks provide a vital mechanism for ensuring that disruptive technologies propagate beyond their initial pioneer locations. Our results thus complement the insights of Kalyani et al. (2023), who highlight the concentrated geographic origins and slow diffusion of disruptive technologies.

We then shift our focus to the firm level to examine whether the patent-level effects identified earlier matter for firm-level outcomes. Our analysis reveals that the innovation activities of social peers and labor-flow-based peers are strong predictors of future citations for focal firms, with elasticities of 0.099 and 0.089, respectively. When considering the total effects—focal firms' overall patenting activities, the elasticities are even higher, at 0.124 and 0.118, respectively.[2] These relationships remain robust even after accounting for production and technology-based peer networks, underscoring the importance of social ties and labor

[2]Our estimates lie well within the common range from 0.01-0.3 for knowledge spillovers (Jaffe et al. 1993, Bloom et al. 2013).

flows in enabling firms to overcome geographic barriers and learn from their distant peers.

Despite the extensive set of firm-level controls and fixed effects included in our baseline specification, unobservable characteristics—such as shared preferences, cultural alignment, or strategic complementarities between focal firms and their peers—could still drive our findings of peer effects. To address these concerns and establish causality, we follow the existing literature and employ state-level variation in R&D tax credits as an instrumental variable (IV) for peers' innovation activities (Wilson 2009, Bloom et al. 2013, Lucking et al. 2018, Arora et al. 2021, Liu and Ma 2024). Prior research shows that state tax credits are largely exogenous to the underlying economic environment and, therefore, can be considered quasi-random in their assignment.

We begin by confirming that an increase in peers' user costs of R&D leads to a corresponding decline in their innovation activities, validating the relevance of the instrument. Two-stage least squares (2SLS) regressions show that increases in patent activities by social peers ($SocialPeer_Pat$) and labor flow-based peers ($LaborFlowPeer_Pat$) boost focal firms' direct citations to these peers with elasticities of 0.075 and 0.121, respectively. The total effects on focal firms'patenting activities, regardless of whether direction citations were made to peers, are even larger, with elasticities of 0.084 and 0.152, respectively. Taken together, our results provide strong evidence that social ties and labor flows promote knowledge spillovers beyond geographic proximity and operate through channels distinct from the production-based and technology-based networks.

In the final section of our paper, we examine the characteristics of focal counties to better understand the factors that enable certain locations to more effectively leverage social and labor flow-based peers for enhanced learning and innovation. Our analysis reveals that focal counties with a higher proportion of local tech workers, higher levels of income and education, a higher ratio of working-age individuals, and stronger economic connectedness (Chetty et al. 2022a) benefit more from social ties and labor flow-based knowledge spillovers.

These findings underscore the uneven distribution of innovation spillovers, which dispro-

portionately favor more privileged and economically developed regions. However, they also point to a pathway for addressing these disparities: policies aimed at fostering cross-class and cross-sectoral interactions can help bridge the gap and enable less advantaged regions to better participate in and benefit from innovation spillovers. By encouraging inclusivity and collaboration across socioeconomic and professional boundaries, such policies have the potential to democratize access to the innovation ecosystem and reduce regional inequalities.

This paper makes several contributions to the literature. First, we advance the ongoing debate on the localization of knowledge spillovers. A large volume of literature (e.g., Jaffe et al. 1993, Audretsch and Feldman 2004, Catalini 2018, Atkin et al. 2022, Roche et al. 2024) shows that knowledge spillover decays rapidly with geographic distance. On the other hand, Keller (2002) and Griffith et al. (2011) document a decline in distance decay rate in recent decades, suggesting that the flow of ideas can go beyond geographic barriers as communication and travel costs fall. In particular, Bailey et al. (2018) shows that higher levels of social connectedness are positively correlated with patent citations and migration flows between counties.

Our paper provides the first systematic causal evidence of the roles of social ties and labor flows in facilitating knowledge spillovers over long distances. We show that these mechanisms not only enhance direct citations but also stimulate broader innovation activities at the firm level. Importantly, we find that these long-distance spillovers are both statistically significant and economically meaningful, with magnitudes comparable to those of geographically localized spillovers. Our findings complement the geographical proximity-based view of spillovers by proposing alternative dimensions of proximity—namely, social connections and labor flows.

Second, we contribute to the literature on urban economics, economic geography, and innovation by emphasizing the critical role of social and professional networks in the diffusion of innovation, particularly for disruptive technologies. Prior research has documented the persistent advantages of specific urban areas in entrepreneurship and innovation, often

attributing these advantages to agglomeration economies and localized knowledge spillovers (Glaeser et al. 2015, Moretti 2021, Kalyani et al. 2023). Our study offers a complementary perspective, underscoring how social networks and labor mobility enable knowledge diffusion across spatial boundaries, thereby mitigating the limitations of geographic isolation. Through focal county welfare analyses, we identify key factors—such as a higher proportion of local tech workers, strong economic connectedness, and favorable demographic composition—that enable regions to more effectively harness distant knowledge spillovers. Notably, we find that innovation spillovers disproportionately benefit more privileged regions, suggesting that policies fostering cross-class interactions can help narrow these disparities, thereby promoting more equitable regional development.

Third, our study adds to the ongoing debate on the impact of non-compete agreements on firm outcomes. Proponents argue that these restrictive agreements are essential for protecting firms' intellectual property and encouraging investment (Barnett and Sichelman 2020). Opponents, however, document that non-compete agreements can stifle innovation, hinder regional growth (Gilson 1999, Marx et al. 2009), and negatively affect workers by limiting their career mobility and bargaining power (Johnson et al. 2023, Starr et al. 2021). Notably, Jeffers (2023) found that while increases in the enforceability of non-compete agreements raised incumbent firms' investment in physical capital, they simultaneously reduced new firm entry, contributing to declining business dynamism.

We contribute to this debate by quantifying a critical but overlooked cost of non-compete agreements: the substantial reduction in innovation spillovers caused by diminished labor market fluidity. Our findings highlight the essential role of labor mobility in facilitating both regional and interregional knowledge exchange, underscoring its importance for fostering innovation and economic growth.

Lastly, we also contribute to the literature emphasizing the importance of social interactions in various economic and finance contexts.[3] Prior research highlights the critical role

[3]For papers on social interactions and economic outcomes, see, for example, Leamer (2007), Bailey et al. (2018, 2019, 2020, 2021), Chetty et al. (2022a,b). Studies on social interactions and finance include Kelly

of physical proximity in fostering collaboration and innovation, while recent papers have extended the concept of proximity beyond geographic distance, showing that reduced travel time lowers the cost of information acquisition.[4] Our findings enrich this literature by showing that social networks and labor flows are powerful channels for facilitating the exchanges of innovative ideas beyond physical proximity.

This paper is organized as follows. In Section 2, we describe data sources, the construction of key variables, summary statistics, and a motivating example. Section 3 outlines our empirical estimation strategy, presenting both firm-to-firm regressions and focal firm-level analyses. We also delve into the underlying mechanisms, examining the role of non-compete agreement enforceability and the diffusion of disruptive technologies. This section concludes with county-level welfare analyses, highlighting the characteristics of counties that benefit most from knowledge spillovers facilitated by social networks and labor flows. Finally, Section 4 concludes with a discussion of our key findings and broader policy implications for understanding knowledge spillovers and fostering innovation.

2 Data and Descriptive Statistics

2.1 Data Sources

We focus our attention on publicly listed firms in the United States and combine datasets from different sources. We first obtain firm-level granted patents between 1926 and 2020 from Kogan et al. (2017).[5] Patent citations and inventor information between 1975 and 2020 are

and O'Grada (2000), Duflo and Saez (2002, 2003), Hong et al. (2004, 2005), Brown et al. (2008), Cohen et al. (2008, 2010), Shive (2010), Kaustia and Knüpfer (2012), Lerner and Malmendier (2013), Shue (2013), Hvide and Östberg (2015), Pool et al. (2015), Heimer (2016), Ahern (2017), Crawford et al. (2017), Maturana and Nickerson (2018), Hong and Xu (2019), Ouimet and Tate (2020), Huang et al. (2021), Huang (2023), and Gerritzen et al. (2024). See Kuchler and Stroebel (2021) for a review of recent papers in social finance.

[4]For example, Bernstein et al. (2016), Da et al. (2021), Catalini et al. (2020),Chen et al. (2022), and Pauly and Stipanicic (2022).

[5]The researchers have regularly updated their dataset, extending to more recent years. For more details, please see https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data.

directly derived from the official website of the United States Patent and Trademark Office. We merge the datasets with the unique patent number and geo-code each patent using its lead inventor's county FIPS code. We assume a firm has an R&D team in a given county if its lead inventors are located there. We define a peer firm as the one whose primary business is in the same three-digit SIC code as the focal firm.

To measure social ties between the R&D locations of a focal firm and its peers, we use *Social Connectedness Index* (*SCI*) between two U.S. counties. This measure, developed by Bailey et al. (2018), is the scaled total number of Facebook friendship links between any two U.S. counties (as of April 2016).[6] As the world's largest online social networking service, Facebook's scale and the relative representativeness of its user body make SCI a comprehensive measure of the geographic structure of U.S. social networks. Facebook had more than 2.1 billion monthly active users globally and 239 million active users in the United States and Canada as of 2017. This represents 68% of the adult population and 79% of online adults in the United States (Duggan et al. 2016). Facebook usage rates among U.S.-based online adults were relatively constant across various demographics and locations. Bailey et al. (2018, 2019, 2020, 2022), Kuchler et al. (2021, 2020), and Rehbein et al. (2020) provide evidence that friendships observed on Facebook are a good proxy for real-world connections. Moreover, Bailey et al. (2018) show that social connections across regions are persistent and argue that SCI is a reasonable proxy for historical social connectedness between regions.

We use the quarterly job-to-job (J2J) flow statistics from the U.S. Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) database to capture labor flows across different regions. The LEHD data has been available since 2000 and provides estimates of the workers' job transition probabilities across different industries and states (see Hyatt et al. 2014, Hahn et al. 2017). We average the quarterly values to annual frequencies to reduce seasonality effects and be consistent with our main data.

In robustness checks, we control for other types of cross-firm linkages that might facilitate

[6]The measure has a maximum value of 1,000,000, which is assigned to the Los Angeles to Los Angeles county pair.

knowledge spillovers. We obtain firms' supplier-customer links from Compustat to proxy for firms' production networks. Firms' technological similarities are borrowed from Lee et al. (2019), which spans from 2000 to 2010. Other firm-level financial controls come from Compustat. Our main sample spans from 2000 to 2020. The sample is shortened to ending in 2010 whenever we control for firms' technology peers based on their technological similarities.

2.2 A Motivating Example

To illustrate our conceptual framework, we start with a motivating example. DocuSign is a software company that allows organizations to manage electronic agreements. It has an R&D lab in King County, Washington State. In March 2010, it filed a patent on systems and methods for document management transformation and security. Five years later, an industry peer called Shoobx, an equity management platform that was later acquired by Fidelity, built upon DocuSign's patent and filed a new one on computer-guided corporate governance with document generation and execution. Shoobx's patent was filed in Rockingham County, New Hampshire State. Geographically speaking, the two companies are far away from each other. Yet, in the social dimension, they are highly connected.

Figure 1 is a heatmap that shows the *Social Connectedness Index* of King County with the rest of the United States. The darker the color, the more connected the counties are. The heatmap shows that the two companies are located in regions with strong social ties. They also have higher labor flows. Both might explain the knowledge spillovers from DocuSign to Shoobx, as embodied in the patent citation.

3 Empirical Strategy

3.1 Pairwise Regression

We test whether stronger social ties and higher job flow probabilities are associated with greater future pairwise patent citations. We construct a pairwise sample at the focal-county–friend-county level to align more closely with the granularity of the SCI measure. Specifically, for an R&D lab of firm i in county m,[7] we pair it with an R&D lab of peer firm j in county n, for all peer firms in the same three-digit SIC industry and all counties associated with a peer firm's R&D labs. Additionally, we include an R&D lab (for both the focal firm and the peer firm) only for the period starting from the year when the lab first filed a successful patent. Finally, we drop all within-state pairs and the pairs between firms sharing at least one common R&D lab county.

Table 1 reports summary statistics for the key variables in our pairwise sample. The knowledge spillover measure, $CiteNum_{i,m,j,n,t}$, counts the number of times patents from focal firm i in county m at year t cite patents from peer firm j in county n at year $t-3$ and has a mean of 0.00025 and standard deviation (SD) of 0.044. The social interaction variable, $SCIShare_{m,n} = \frac{SCI_{m,n}}{\sum_n SCI_{m,n}}$, has a mean of 0.0012 and an SD of 0.0024. Because its distribution is highly skewed (skewness = 9), we use its decile rank in regressions. Similarly, $JobFlow_{i,m,j,n,t-3}$—the job transition probability between the focal firm's two-digit NAICS industry in county m's state and the peer firm's in county n's state—has a mean of 0.001 and an SD of 0.0018; we also use its decile rank to mitigate the influence of extreme values.

We estimate the following regression models:

$$\ln\left(CiteNum_{i,m,j,n,t}\right) = \beta_1 SCIShare_{m,n} + \beta_2 JobFlow_{m,n,t-3} + \omega X_{t-3} + \epsilon_{i,m,j,n,t}. \quad (1)$$

[7] We assign one R&D lab per county for a given firm. If a firm has multiple R&D labs in the same county, we aggregate their patents and citations.

X_{t-3} include firm-level controls: firm size, book-to-leverage ratio, fixed assets, R&D intensity, profitability (measured for both the focal firm and the peer firm), and focal firm, friend firm, and year fixed effects. Standard errors are two-way clustered at firm-pair and year.

Results are presented in Table 2. All coefficients are multiplied by 10^4. In column 1, we include the inverse of distance between two counties as a measure of geographic proximity. Its coefficient is -0.0927 and insignificant, indicating that geographic proximity is not meaningfully related to out-of-state innovation spillovers.

In column 2–3, we add measures of social connectedness and job flow probability, respectively. Both measures are positive and highly significant. In terms of economic magnitude, a one-decile-rank increase (e.g., from decile rank 5 to 6) is associated with an increase in (logged) citations by 0.2277 and 0.1599, or 20.14% and 14.33% relative to the sample average of pairwise citations, respectively. In column 4, we include all three pairwise measures simultaneously and find that the coefficients on social ties and job flows remain significant.[8] In column 5, we adopt a more stringent fixed effects specification by including the year and firm-pair fixed effects and find the effects of social ties and job flow remain highly significant.

To further provide robustness for our results, we run Poisson regressions of pairwise citations on social ties and job flows. The results are presented in Appendix Table A.2. The findings are very similar to the ordinary least squares regression in Table 2, even in terms of economic magnitudes. For example, based on column 2–3 in Table A.2, an increase from decile rank s to $s+1$ in $SCIShare$ and $JobFlows$, while other variables are held constant, are associated with an relative 24.04% and 14.93% increase in the number of citations, respectively.

[8]The coefficient on inverse distance turns significant when $SCIShare$ is added. It is common for geographic proximity to show up with wrong sign when measures of social proximity are added. See **?** for an example.

3.1.1 Moderating Effects of Non-Compete Enforceability

We further explore how variations in state-level non-compete clause enforceability moderate the effects of social interaction and labor flows on innovation spillovers. Non-compete clauses (NCCs) are contractual provisions that restrict employees from working for competitors within a specified time period after leaving their current employer. The enforceability of these clauses varies across states and over time due to court rulings. During our sample period, there were nine state-level court rulings that affected NCC enforceability, as documented by Jeffers (2023), with some strengthening and others weakening enforcement.

To examine this, we create two indicator variables: $TreatedPost_{i,t-3}$ equals one (minus one) if the focal firm i's state has had a court ruling increasing (decreasing) NCC enforceability before year $t-3$, and zero otherwise. Similarly, $TreatedPost_{j,t-3}$ is defined for peer firm j. We then interact these indicators with our measures of social ties ($SCIShare_{m,n}$) and labor flows ($JobFlow_{i,m,j,n,t-3}$).

Table 3 presents the results. We find that increased NCC enforceability significantly weakens both the labor flow and social network channels of knowledge spillovers. When the peer firm's state strengthens NCC enforcement, the effect of labor flows on innovation spillovers drops by 0.1698 (significant at 1% level), entirely offsetting the baseline effect of labor flow (coefficient of 0.1511). Similarly, when the focal firm's state increases enforcement, the effect decreases by 0.1030 (significant at 1% level), a 74% drop in the effect of job flow. The interaction effects with social ties show a similar pattern, with coefficients of -0.1776 and -0.0862 for peer and focal firm state enforcement, respectively.

These findings can be explained through several economic mechanisms. First, stronger NCCs create direct barriers to worker mobility, reducing both actual and potential job transitions. Jeffers (2023) provides evidence that NCC enforceability increase the employee retention rate, so stronger NCCs in a peer firm's state could lower the outflow of workers. Meanwhile, stronger NCCs in the focal firm's state could render the focal state as a less desirable state to move into. Altogether, this makes the labor channel less effective for

knowledge transmission. The stronger effect from peer firm's state enforceability (-0.1698 vs -0.1030) suggests that restrictions on knowledge outflows are particularly binding.

Second, the weakening of social ties' effects reveals that NCCs affect not just formal labor mobility but also informal knowledge sharing. This could occur because employees become more cautious about informal discussions with former colleagues due to legal risks, and professional networks become less valuable when job mobility is restricted.

The fact that both job flow and social ties effects weaken suggests these channels are complementary. Labor flows help maintain and strengthen social networks, and when labor mobility is restricted, social networks become less effective for knowledge transmission. These results complement prior work showing that non-compete enforcement affects inventor mobility (Jeffers 2023). We extend this literature by demonstrating that NCCs not only affect formal labor market channels but also impede informal knowledge transmission through social networks.

Our results has important implications for ongoing policy debates about non-compete enforcement. Our estimates reveal that stronger NCC enforcement nullifies the innovation spillover benefits of labor mobility—the effect of job flows on innovation spillover is completely eliminated when the peer firm's state strengthens NCC enforcement (-0.1698 vs. 0.1511) and is largely reduced when the focal firm's state does so (-0.1030 vs. 0.1511). These findings contribute to the current policy discourse, exemplified by the recent judicial challenge to the FTC's proposed nationwide ban on non-competes. While proponents argue that NCCs are necessary to protect firm investments and trade secrets, our results quantify a significant cost: the dramatic reduction in innovation spillovers that typically arise from labor market fluidity.

3.1.2 Disruptive Technology

Kalyani et al. (2023) document that a small number of disruptive technologies drive a disproportionate share of innovation activity. Building on their insights, we expect that these

disruptive technologies might also exhibit stronger effects of labor flows and social ties on knowledge spillovers, as they represent fundamental breakthroughs that spawn subsequent innovations.

To investigate this, we follow Kalyani et al. (2023) to identify two types of patents: disruptive technology patents and pioneer patents within disruptive fields. We create two indicator variables: $Disruptive_{j,t-3}$ equals one if the peer firm filed a patent in disruptive technology in year $t-3$, and zero otherwise; $Pioneer_{j,t-3}$ equals one if the peer firm's patent filed in year $t-3$ is a pioneer patent in its disruptive technology category. The disruptive and pioneer peer patents represent 25.3% and 17% of our sample respectively. We run regression (1), now interacting these two indicator variables with social interaction and job flow.

Table 4 presents striking evidence that the innovation spillover effects are primarily driven by disruptive and pioneering technologies. The interaction effects with social ties ($SCIShare_{m,n}$) are particularly strong. For disruptive technologies, the coefficient on $SCIShare_{m,n} \times Disruptive_{j,t-3}$ is 0.2500, and for pioneer patents, the coefficient on $SCIShare_{m,n} \times Pioneer_{j,t-3}$ is 0.3052, both statistically significant. These effects are about two to three times larger than the effect of $SCIShare_{m,n}$ for other technologies, which is 0.1303–0.1280. This suggests that social networks play a disproportionately important role in facilitating knowledge spillovers for disruptive and pioneering technologies.

The results for labor mobility ($JobFlow_{i,m,j,n,t-3}$) further reinforce this pattern. The coefficients on $JobFlow_{i,m,j,n,t-3} \times Disruptive_{j,t-3}$ and $JobFlow_{i,m,j,n,t-3} \times Pioneer_{j,t-3}$ are 0.5279 and 0.5437, respectively, both statistically significant. Given that the baseline coefficient on $JobFlow$ is near zero and insignificant, this suggests that the effects of labor mobility on knowledge spillovers are entirely driven by firms developing disruptive technologies. Economically, these effects are meaningful. For disruptive and pioneer technologies, a one-decile-rank increase in $JobFlow$ is associated with an approximately 31.57% and 33.58% increase in spillovers relative to the sample average.

Overall, the stronger effects observed suggest that social and professional networks, as

well as talent flows, are particularly effective mechanisms for the diffusion of high-impact innovations. These results build on the findings of Kalyani et al. (2023), who highlight the concentrated geographic origins and slow diffusion of disruptive technologies. Our evidence underscores the critical role of social and professional networks in overcoming the spatial and organizational barriers to innovation diffusion, providing a complementary perspective on how disruptive technologies propagate beyond their initial pioneer locations.

3.2 Focal Firm-level Regressions

After establishing the micro foundation for the diffusion of distant knowledge, we now move to the focal firm level and investigate whether the granular effects identified earlier would aggregate to have a significant impact.

To formally test this, we construct two aggregate peer innovation measures. The first is social peer innovation. Specifically, for firm i in R&D location county m of state s in year t, its social peer innovation is defined as follows:

$$SocialPeer_Pat_{i,m,t} = ln\left(\sum_{\mathrm{n}}\left(\frac{SCI_{m,n}}{\sum_{\mathrm{n}} SCI_{m,n}} \times \sum_{\mathrm{j}} \mathrm{Pat_{j,n,t}}\right)\right) \tag{2}$$

$\mathrm{Pat_{j,n,t}}$ is the number of patents of peer firm j in county n year t. $\mathrm{SCI}_{m,n}$ is the *Social Connectedness Index* between county m and n. $\frac{SCI_{m,n}}{\sum_n SCI_{m,n}}$ captures the relative importance of county n in the social network of county m. We exclude peers with the same-state headquarters or sharing R&D locations with the focal firm to isolate the confounding effects of home bias and within-firm knowledge transfer. By construction, the social peer innovation measure places more weight on peer inventors sharing strong social ties with the focal firm location.

The second key variable is labor flow-based peer innovation, which is constructed in a similar way by replacing the SCI index with job flow probabilities across jobs and states:

$$JobFlowPeer_Pat_{i,m,t} = ln\left(\sum_{l}\left[JobFlow_{s,l,t} \times \sum_{\text{j}} \text{Pat}_{j,l,t}\right]\right) \tag{3}$$

where $\text{Pat}_{j,l,t}$ is the number of patents for peer firm j in state l year t. $JobFlow_{s,l,t}$ is the workers' job transition probability from state l to state s in the same three-digit SIC industry in year t. This measure varies at the firm-year-state level and puts more weight on peers who share higher labor flows with the focal firm county.

In addition to the two key variables, we also control the traditional inverse distance-weighted number of peer patents, i.e., $SpatialPeer_Pat_{i,m,t}$ and firm-level financials: firm size, book-to-leverage ratio, fixed assets, R&D intensity, and profitability (ROA). In robustness checks, we also include a firm's production network-weighted peer innovation, $ProdPeer_Pat_{i,m,t}$, and technological similarity-weighted peer innovation, $TechPeer_Pat_{i,m,t}$.

We focus on two outcome variables. The first is $ln(FocalCiteNum_{i,m,t})$—the logarithm of focal firm $i's$ number of citations in county m year t made to patents filed by all peer firms in year $t-3$. By counting the number of direct citations the focal firm made to all peer firms, this measure captures the direct effect of knowledge spillovers.

The second outcome, $ln(FocalPat_{i,m,t})$, is the logarithm of focal firm $i's$ citation-weighted number of patents produced in county m year t. We use this measure to capture more broad-based knowledge spillovers, hence the total effect. Inventors from closely connected regions (either through strong social ties or high labor flows) engage in chats and discussions frequently, which may spark new ideas and solutions that eventually become inventions. However, inventors may not necessarily cite the work of other inventors despite being inspired by them. Direct citations capture a particular set of knowledge obtained from peers. Other dimensions of knowledge, such as innovation strategies, new ways of thinking, and attention to an emerging technology or phenomenon, could all benefit from close peer interactions and higher labor flow, which help the creation of new patents.

Table 1 presents summary statistics on these key variables. On average, a focal firm's R&D lab in a focal county made 0.1 log numbers of citations to peer patents filed three

years ago and produced 0.29 log numbers of citation-weighted new patents. Its spatial peers generated 0.95 log numbers of patents annually, while social peers and job flow-based peers produced 1.06 and 2.15 log numbers of patents, respectively.

Using these measures, we estimate the following empirical specification:

$$ln(FocalInnovation_{i,m,t}) = \alpha + \beta ln(Peer_Pat_{i,m,t-3}) + \omega X_{it-3} + \lambda Year_t + \gamma State_s + \epsilon_{i,m,t}, \quad (4)$$

where the dependent variable is one of the two outcomes: $ln(FocalCiteNum_{i,m,t})$ or $ln(FocalPat_{i,m,t})$, and $ln(Peer_Pat_{i,m,t-3})$ represents various measures of industry peer innovation in year $t-3$.

We take a three-year lag to account for the fact that it takes time for an innovative idea to materialize into an invention (He and Tian (2013)). In addition to the two key peer innovation measures introduced earlier, i.e., $SocialPeer_Pat_{i,m,t-3}$ and $JobFlowPeer_Pat_{i,m,t-3}$, we also control the traditional distance-based peer innovation measure, i.e., $SpatialPeer_Pat_{i,m,t-3}$, which is the inverse distance-weighted number of peer patents filed in year $t-3$. X_{it-3} includes several focal firms' financials from three years ago: firm size, book-to-leverage ratio, fixed assets, R&D intensity, and profitability. $Year_t$ and $State_s$ represent year and state fixed effects, respectively. All standard errors are clustered at the 3-digit SIC by year level.

Results are presented in Table 5. In panel A, we examine the direct effect, and in panel B, we turn to the total effect. In both panels, we independently include the three peer innovation measures in Columns (1) to (3). Then, in the last two columns, we include them in one specification for comparison, with Column (5) having the most comprehensive set of fixed effects. $SocialPeer_Pat_{i,m,t-3}$ and $JobFlowPeer_Pat_{i,m,t-3}$ are highly correlated, with a correlation coefficient of 0.81. Given the high correlation between the two measures, we use an alternative measure of $JobFlowPeer_Pat_{i,m,t-3}$ in Columns (4) and (5), which is orthogonalized with respect to $SocialPeer_Pat_{i,m,t-3}$. All variables are standardized, and their magnitude can be directly compared against one another.

The first column in both panels confirms the findings in the prior literature. Along the

spatial dimension, knowledge spillovers are fairly localized and decay quickly with physical distance. Geographically close peers have a disproportionately larger impact on knowledge spillovers. Turning to column (2), when we switch to the social dimension, SCI-weighted peers produce an equally strong influence in facilitating knowledge spillovers. Column (3) includes job flow-based peer innovation, whose coefficient is highly significant and slightly larger than that generated by spatial peers.

The message remains fairly similar when we include all measures and an extensive set of fixed effects in Column (5). Social ties and job flow-based peers' innovation strongly predict future citations in focal firms, with elasticities of 0.099 and 0.089, respectively. The total effects in Panel B are even larger, with elasticities of 0.124 and 0.118, respectively. Such results suggest that social ties and labor flows help firms overcome geographic barriers and facilitate distant knowledge spillovers that are conducive to innovation.

3.2.1 IV Strategy

Despite an extensive set of firm-level controls and fixed effects in our baseline specification, our results can still be driven by unobserved characteristics, such as shared preferences and perspectives between a focal firm and its peers, which simultaneously induce inventors' close social interactions, higher job flows across regions, and new patents.

To establish causality, we follow the literature and use state-level variation in tax credits as an instrument for peers' innovation activities (Wilson (2009), Bloom et al. (2013), Lucking et al. (2018), Arora et al. (2021), Liu and Ma (2024)). Different states have different levels of R&D tax credits and corporation tax, which differentially affect firms depending on their cross-state distribution of R&D activities. The literature has shown ample evidence suggesting that the state tax credits are largely randomly assigned and are uncorrelated with the underlying economic environment. Therefore, the state-level tax credits induce exogenous changes in the firm-year-state-specific user cost of R&D (based on a firm's inventor locations and capital structure).

We compute the firm-specific user cost of R&D following Lucking et al. (2018). Essentially, the state R&D tax credits reduce the marginal cost of R&D, but does not affect the benefit. When the user cost rises, corporate innovation investment falls. As a result, when the user cost for distant social peer locations increases, peer innovations will decrease. If SCI- and job flow-weighted peers really play a causal role in knowledge spillovers, we would also witness a same-direction change in focal firms' innovation activities. As a result, the coefficient β is expected to be positive and significant.

We first validate the negative effects of R&D user cost on firm innovation in Table 6. There are two types of R&D tax credits, one from the state, the other from the Federal government.[9] Both could translate into a firm-specific R&D user cost. But in our context, the federal level tax credits don't seem to significantly influence since they don't vary at the geographic level. Nevertheless, we follow the literature and include both types of R&D user costs in predicting peer firms' innovation. The estimated coefficient implies that when the user cost of a firm's R&D increases from the 10th to the 90th percentile, its innovation will drop by 6.7%.

To create instruments for the peer patents measures used in regression (4), we calculate aggregate peer R&D tax credits weighted by inverse distance ($SpatialPeer_Credit$), SCI share ($SocialPeer_Credit$), and job flow probability ($JobFlowPeer_Creit$). Table 7 presents the second stage of our IV results. Specifically, in Panel A, increases in the patent activities by social peers and job flow-based peers raise focal citations with elasticities of 0.075 and 0.121, respectively. In Panel B, the total effect is slightly large, with elasticities of 0.084 and 0.152, respectively. The estimated magnitudes of relevant innovation measures are comparable to our OLS results and to the estimated magnitude of spatial peers. Taken together, we find that social ties and labor flows transcend geographic barriers and facilitate knowledge spillovers over long distances. Moreover, they seem to operate through channels distinct from the spatial networks.

[9]The federal tax credits induce a firm-specific user cost of R&D because the definition of what qualifies as allowable R&D for tax purposes depends on a firm-specific "base".

3.2.2 Robustness Checks

We conduct two sets of robustness checks to test the sensitivity of our firm-level results. First, we additionally construct two other peer innovation measures in the industry that could potentially facilitate knowledge spillovers. Specifically, they are $ProdPeer_Pat_{i,m,t-3}$— a production network weighted peer innovation measure using Compustat supplier-customer link and $TechPeer_Pat_{i,m,t-3}$— a technology network weighted peer innovation measure with firms' pairwise technology similarities (Bloom et al. (2013), Lee et al. (2019)). The OLS results are presented in Table A.3, and IV results in Table A.4.

In both tables, the coefficients of our key peer innovation measures, i.e., $SocialPeer_Pat_{i,m,t-3}$ and $JobFlowPeer_Pat_{i,m,t-3}$, remain highly stable and significant. Their magnitudes are also highly similar to our baseline results. For example, in Panel A of Table A.4, increases in the patent activities by social peers and job flow-based peers raise focal citations with elasticities of 0.079 (vs.0.075) and 0.133 (vs.0.121), respectively. The influences grow even stronger when we turn to total effects in Panel B– increases in the patent activities of social peers and job flow-based peers boost focal patent activities with elasticities of 0.132 (vs.0.084) and 0.208 (vs.0.152), respectively.

Production network-based peer innovation also positively affects a focal firm's innovation activities. Since our production network measure is based on Compustat's supplier-customer link, the positive spillover effect we observe is unidirectional and likely arises from the downstream market feedback to the upstream suppliers. Technology similarity-weighted peer innovation, on the other hand, significantly reduces a focal firm's innovation. Because we focus on the same three-digit SIC industry peers, an increase in a close tech peer's innovation produces competing effects– a positive knowledge effect vs. a negative market competition effect (Bloom et al. 2013). In our context, it seems that a competition effect dominates.

Second, we replicate our baseline results with alternative peer measures to more closely align with our firm pairwise regressions that focus on out-of-state peers. Specifically, we now use $SocialPeer_Pat^{OutState}_{i,m,t-3}$ and $JobFlowPeer_Pat^{OutState}_{i,m,t-3}$ as our alternative key measures. The

OLS results are reported in Table A.5, and IV results are in Table A.6.[10] Our results remain highly robust to these alternative measures, further validating our key findings.

3.3 Welfare Analyses Based on Focal County Characteristics

Our analyses have shown that social ties and job flow-based peers play a crucial role in helping firms overcome geographic barriers and, therefore, facilitate distant knowledge spillovers. In this section, we delve deeper into the focal characteristics to gain a better understanding of the factors that allow a location to better leverage the two types of peers to enhance learning and boost innovation.

Regional Diversity and Heterogeneity. Existing spatial theories of innovation and knowledge diffusion underscore the critical role of regional diversity in fostering innovation, particularly unconventional and groundbreaking ones (Duranton and Puga 2001, Berkes and Gaetani 2021). The central argument is that regions characterized by a diverse population—where individuals possess varied origins, experiences, and professional backgrounds—create fertile ground for the exchange of heterogeneous information and perspectives. This confluence of diversity, facilitated by spatial proximity, serves as a catalyst for novel ideas, cross-disciplinary collaboration, and creative problem-solving, all of which are essential drivers of innovative activity.

In contrast, regions dominated by a more homogenous workforce may face limitations in knowledge generation and creativity, as the lack of diversity constrains the range of perspectives and ideas available for recombination. Without external inputs or out-of-region knowledge flows, such regions are likely to exhibit lower levels of productivity in innovation.

In this context, we aim to empirically investigate whether the reliance on distant social ties and labor flows for knowledge acquisition and diffusion is more pronounced in regions

[10] Because $SocialPeer_Pat_{i,m,t-3}^{OutState}$ is highly correlated with $SpatialPeer_Pat_{i,m,t-3}^{OutState}$. To make sure that we are not picking up the spatial aspect of knowledge spillovers and our estimates are not biased due to multicollinearity, in Columns (4) and (5) of both tables, we first orthogonalize $SocialPeer_Pat_{i,m,t-3}^{OutState}$ with respect to $SpatialPeer_Pat_{i,m,t-3}^{OutState}$, and then plug the residualized measure into the regressions.

with a higher proportion of locally rooted workers—those born and raised within the region. Specifically, we hypothesize that regions with a less diverse workforce may compensate for their limited internal knowledge variety by leveraging external social networks and labor mobility to access and integrate new ideas from distant sources. This reliance on external connections could provide a crucial mechanism for knowledge transfer and innovation in regions where local diversity is insufficient to sustain vibrant knowledge ecosystems.

Regional Wealth and Income. The socio-economic status of a location also influences its ability to innovate. It has been well established that higher regional income levels provide both the resources and the demand necessary to support innovation (Change 1990, Fagerberg 1994). Wealthier regions can allocate greater funding toward R&D activities, advanced infrastructure, and innovation-enabling institutions such as universities and research centers. At the same time, higher disposable incomes create demand for new products and services, incentivizing firms to innovate to capture local market opportunities. Building upon this common wisdom, we further examine whether high-income regions are also better at leveraging distant social ties and labor flows in knowledge diffusion and innovation.

Education and Human Capital. Another important factor in fostering innovation and promoting economic growth is a region's level of human capital (Nelson and Phelps 1966, Cohen et al. 1990, Moretti 2004). Education enhances cognitive skills, problem-solving abilities, and creativity, all of which are essential for generating new ideas and technologies. Moreover, a well-educated workforce is better equipped to absorb, adapt, and reapply external knowledge, fostering incremental and radical innovations. Therefore, regions with higher levels of education are more productive in innovation. We take one step further and empirically investigate whether more educated regions benefit more from the knowledge spillovers based on distant social ties and job flows. On one hand, in highly educated regions, the marginal benefit of additional knowledge spillovers may be lower because these regions may already possess significant endogenous knowledge and expertise; on the other hand, regions

with a more educated population often have a higher absorptive capacity and are thus better equipped to understand and utilize knowledge brought in through distant social ties and job flows, enabling them to integrate this knowledge into innovative processes more effectively.

Labor Force Participation. The share of the population engaged in the workforce directly may also impact a region's ability to generate and disseminate knowledge (Feyrer 2007). A higher labor force participation rate ensures that more individuals contribute to productive activities, including knowledge creation and innovation. Additionally, regions with a high share of active workers may experience greater interaction among individuals, fostering knowledge spillovers and collaborative problem-solving. Yet, it remains an empirical question on whether locations with a larger share of the working population would likewise benefit more from distant knowledge spillovers arising from stronger social ties and higher job flows.

Economic Connectedness. Lastly, we focus on the role of a region's economic connectedness in harnessing distant knowledge spillovers. Economic connectedness, defined as the degree of interaction between individuals from low- and high-income groups, has been identified as a strong predictor of upward income mobility (Chetty et al. 2022a). Social networks are often stratified by socioeconomic class, as individuals tend to form friendships with those of similar income levels. However, using privacy-protected data on 21 billion friendships from Facebook, Chetty et al. (2022a) demonstrate that children growing up in communities with higher levels of economic connectedness—characterized by significant cross-class interactions—are substantially more likely to escape poverty.

Building on this evidence, we hypothesize that higher economic connectedness, by fostering friendships and exchanges across class lines, enhances the diversity of knowledge exchange within a region. Such diversity is essential for innovation, which thrives on the novel recombination of ideas from varied perspectives. Furthermore, cross-class interactions may increase individuals' absorptive capacity—their ability to recognize, assimilate, and apply external

knowledge—thereby positioning them to better leverage distant knowledge spillovers. In this context, regions with higher economic connectedness are not only more likely to stimulate creative inventions but also to capitalize on external knowledge flows, driving sustained innovation and growth.

In sum, we consider the following county-level characteristics: (1) the ratio of local tech workers, (2) median income, (3) average years of schooling, (4) the ratio of working population, and (5) economic connectedness.[11]

We begin by classifying focal counties into two groups: above median (high) and below median (low) based on the aforementioned dimensions. We then create a dummy variable *FocalCounty* that takes a value of one if the focal county's corresponding characteristics fall above median and zero otherwise. The modified equation 4, with the same set of controls and fixed effects as before, is estimated as follows:

$$\begin{aligned} ln(FocalInnovation_{i,m,t}) = \alpha &+ \beta_1 ln(Peer_Pat_{i,m,t-3}) + \beta_2 FocalCounty_{i,m,t-3} \\ &+ \beta_3 ln(Peer_Pat_{i,m,t-3}) * FocalCounty_{i,m,t-3} + \omega X_{it-3} \\ &+ \lambda Year_t + \gamma State_s + \epsilon_{i,m,t}, \end{aligned} \tag{5}$$

The results, presented in Table 8, provide insightful evidence on the factors that influence a region's ability to harness knowledge spillovers from distant peers. Column (1) reveals that focal counties with a higher proportion of local tech workers benefit significantly from strong social ties and higher job flows with distant peers. This may be because local working environments in such counties tend to be relatively homogeneous, offering fewer opportunities for exposure to novel perspectives and insights. Consequently, greater innovation occurs when local tech workers engage more frequently with distant peers who provide access to diverse ideas and experiences.

Columns (2) and (3) extend this analysis by showing that wealthier and more educated

[11]Variables in (1) to (4) are obtained from the annual estimates of county-level socio-economic characteristics in the American Community Survey (ACS) between 2000 and 2017. The variable in (5) is obtained from https://www.socialcapital.org (Chetty et al. 2022a).

counties are better positioned to leverage these peer-based channels for learning new knowledge and fostering innovation. This finding aligns with the established understanding that privileged regions—owing to their superior resources, infrastructure, and human capital—are better equipped to capitalize on innovation spillovers. Column (4) highlights another important dimension: counties with a higher proportion of their population in the prime working age range (25–60) are more likely to benefit from these knowledge flows. This demographic typically constitutes the core knowledge workforce, actively engaged in the production, diffusion, and application of knowledge within a county.

Finally, Column (5) uncovers a significant role for economic connectedness: regions with greater interaction across socioeconomic lines benefit more from peer-based innovation spillovers. This finding underscores the importance of cross-class social interactions in enabling the flow of diverse ideas, enhancing absorptive capacity, and fostering a more inclusive innovation ecosystem.

Taken together, these results suggest that while innovation spillovers disproportionately benefit more privileged regions, policies aimed at fostering economic connectedness—by encouraging interactions across class lines—can mitigate these disparities. By broadening access to diverse knowledge pools and promoting inclusive collaboration, such policies hold the potential to democratize the benefits of innovation spillovers and contribute to more equitable regional development.

4 Conclusion

This paper investigates the roles of social ties and labor flows in facilitating knowledge spillovers across long distances. Different from the traditional proximity-based view of knowledge spillovers, we provide causal evidence that knowledge spillovers can transcend geographic boundaries through social networks and labor flows. Using a combination of patent-level pairwise citation analysis and firm-level tests, we demonstrate that these effects

are economically significant. Social ties and job flow-based peers' innovation strongly predict future citations in focal firms, with an elasticity of 0.1 and 0.09, respectively. The effects are even larger for focal firms' total patenting activities, with an elasticity of 0.12 for both peers. We also show that social ties and job flows are especially valuable in the diffusion of disruptive and pioneering technologies that go beyond their initial locations. Together, the evidence underscores the pivotal role that social networks and labor flows play in overcoming spatial barriers to knowledge diffusion.

Our findings have important policy implications. The evidence suggests that increased enforceability of non-compete agreements significantly undermines both the social network and labor flow channels of knowledge spillovers. Furthermore, counties with a higher proportion of tech workers, greater income and education levels, a larger share of the working-age population, and stronger economic connectedness derive greater benefits from knowledge spillovers facilitated by social networks and labor flows. Our findings thus help inform policies aimed at enhancing knowledge flow, fostering innovation, and promoting economic growth.

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Figure 1: Example of Social Connectedness

This figure shows a county-level heatmap of the social connectedness to King County, WA. The focal county is in red, and the darker the colors, the higher the social connectedness of a county to the focal King County. The focal and peer firms are illustrated in purple.

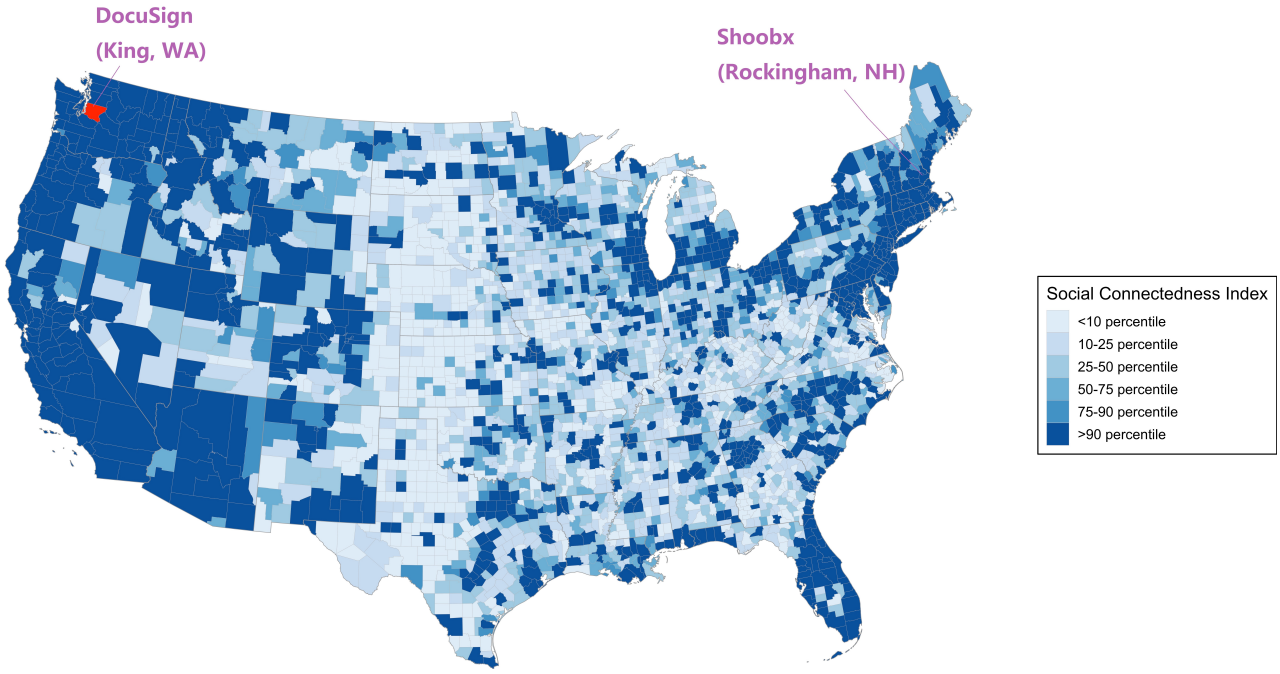


Table 1: Summary Statistics

This table lists the summary statistics of key measures and variables. $CiteNum_{i,m,j,n,t}$, is the logarithm of the number of times the patents produced by the focal firm i in county m and year t cite the patents produced by the peer firm j in county n and year $t-3$. $SCIShare_{m,n}$ is the SCI share between a focal county m and a friend county n, calculated as $\frac{SCI_{m,n}}{\sum_n SCI_{m,n}}$. $JobFlow_{i,m,j,n,t-3}$ is the job transition probability between focal firm i's two-digit NAICS industry in county m's state and peer firm j's two-digit NAICS industry in county n's state. $ln(FocalCiteNum_{i,m,t})$, is the logarithm of focal firm $i's$ number of citations in county m year t to patents filed by peer firms in year $t-3$. $ln(FocalPat_{i,m,t})$, is the logarithm of focal firm i's citation-weighted number of patents filed in county m year t. $SpatialPeer_Pat_{im,t}$ is the inverse-distance-weighted number of peer patents in year t. $SocialPeer_Pat_{im,t}$ is the SCI-weighted number of peer patents in year t. $JobFlowPeer_Pat_{im,t}$ is the job-to-job transition probability (across industries and states) weighted number of peer patents in year t. $ProdPeer_Pat_{im,t}$ and $TechPeer_Pat_{im,t}$ are peer patents weighted by Compustat supplier-customer link and technology similarities, respectively. All peer measures are in logarithm. Refer to Appendix Table A.1 for detailed variable definitions for other variables.

Variable	Obs	Mean	Std. Dev	P5	P10	P50	P90	P95
Pairwise Key Measures								
$CiteNum_{i,m,j,n,t}$	11603769	0.00025	0.044	0	0	0	0	0
$SCIShare_{m,n}$	11603769	0.0012	0.0024	0.00002	0.000046	0.00047	0.0027	0.0044
$JobFlow_{i,m,j,n,t-3}$	10885604	0.001	0.0018	0.000056	0.0001	0.00053	0.0021	0.0032
Firm-level Key Measures								
$ln(FocalCiteNum_{i,m,t})$	419735	.103	.696	0	0	0	0	0
$ln(FocalPat_{i,m,t})$	419735	.293	.77	0	0	0	1.154	2.015
$SpatialPeer_Pat_{im,t}$	419735	.952	1.066	0	.003	.513	2.57	3.11
$SocialPeer_Pat_{im,t}$	419735	1.06	1.29	0	.001	.447	3.072	3.782
$JobFlowPeer_Pat_{im,t}$	419735	2.148	2.362	0	0	1.356	5.789	7.095
$ProdPeer_Pat_{im,t}$	419735	.327	1.571	0	0	0	0	0
$TechPeer_Pat_{im,t}$ (2000-2010)	186162	6.468	3.708	0	0	7.643	10.435	10.872
Firm-level Control Variables								
$ln(FirmSize)_{i,t}$	419448	8.623	2.489	4.128	5.12	8.75	11.723	12.491
$BookLeverage_{i,t}$	419411	.231	.174	0	0	.22	.464	.559
$ln(FixedAssets)_{i,t}$	419327	.178	.146	.021	.039	.133	.38	.49
$R\&DIntensity_{i,t}$	419729	.071	.098	0	.001	.04	.166	.251
$Profitability_{i,t}$	419420	.052	.167	-.255	-.067	.082	.177	.214
$R\&DUserCost_{im,t}^{State}$	301086	.249	.019	.221	.222	.248	.275	.285
$R\&DUserCost_{i,t}^{Fed}$	419735	1.18	.245	.966	.967	1	1.5	1.5
Focal County Characteristics								
$LocalTechWorkers_{m,t}$ (2000-2017)	27179	.096	.025	.057	.067	.095	.129	.138
$Income_{m,t}$ (2000-2017)	27179	46038.76	13417.5	27772	31013	44187	62508	71464
$YearsOfSchooling_{m,t}$ (2000-2017)	27179	12.992	.685	11.925	12.173	12.945	13.857	14.168
$WorkingPop_{m,t}$ (2000-2017)	27179	.522	.05	.433	.46	.529	.574	.587
$EconomicConnectedness_{m,t}$	32030	.841	.162	.585	.64	.828	1.068	1.122

Table 2: Social Ties, Job Flows, and Pairwise Citations

This table presents the regression results of pairwise citations on social ties and job flows. The dependent variable, $\ln(CiteNum_{i,m,j,n,t})$, is the logarithm of the number of times the patents produced by the focal firm i in county m and year t cite the patents produced by the peer firm j in county n and year $t-3$. $SCIShare_{m,n}$ is the SCI share between a focal county m and a friend county n, calculated as $\frac{SCI_{m,n}}{\sum_n SCI_{m,n}}$. $JobFlow_{i,m,j,n,t-3}$ is the job transition probability between focal firm i's two-digit NAICS industry in county m's state and peer firm j's two-digit NAICS industry in county n's state. Decile ranks of $SCIShare_{m,n}$ and $JobFlow_{i,m,j,n,t-3}$ are used in the regression. Standard errors (in parentheses) are clustered by firm-pair and year. Coefficients and standard errors are multiplied by 10^4. $^*p<.1$; $^{**}p<.05$; $^{***}p<.01$.

	Dependent Variable: $\ln(CiteNum_{i,m,j,n,t})$				
	(1)	(2)	(3)	(4)	(5)
$\ln(Distance_{m,n}^{-1})$	-0.0927			-0.3870***	-0.3901***
	(0.0730)			(0.0921)	(0.0941)
$SCIShare_{m,n}$		0.2277***		0.2195***	0.2221***
		(0.0482)		(0.0472)	(0.0475)
$JobFlow_{i,m,j,n,t-3}$			0.1559***	0.1307***	0.1321***
			(0.0408)	(0.0365)	(0.0385)
$RDIntensity_{i,t-3}$	-1.3071	-1.2776	-1.3463*	-1.3077	-1.2398*
	(0.7631)	(0.7592)	(0.7702)	(0.7636)	(0.6529)
$\ln(FirmSize)_{i,t-3}$	-0.4857**	-0.4803**	-0.4842**	-0.4764**	-0.4314**
	(0.1942)	(0.1937)	(0.1943)	(0.1930)	(0.1984)
$BookLeverage_{i,t-3}$	0.6479	0.6620	0.6349	0.6560	0.8837
	(0.4998)	(0.5011)	(0.5000)	(0.5004)	(0.5520)
$\ln(FixedAssets)_{i,t-3}$	-2.4308*	-2.4059*	-2.4857*	-2.4853*	-2.4761*
	(1.2303)	(1.2254)	(1.2231)	(1.2255)	(1.2940)
$Profitability_{i,t-3}$	1.0186**	1.0211**	0.9951**	0.9992**	0.9650**
	(0.3995)	(0.3985)	(0.3993)	(0.3972)	(0.4260)
$RDIntensity_{j,t-3}$	3.2040***	3.2269***	3.1857***	3.2117***	2.1881**
	(0.9480)	(0.9526)	(0.9452)	(0.9494)	(0.8901)
$\ln(FirmSize)_{j,t-3}$	0.3441*	0.3462*	0.3379*	0.3420*	0.1439
	(0.1838)	(0.1835)	(0.1832)	(0.1831)	(0.1557)
$BookLeverage_{j,t-3}$	-0.5802	-0.5581	-0.5909	-0.5651	-0.1238
	(0.5624)	(0.5611)	(0.5622)	(0.5614)	(0.6907)
$\ln(FixedAssets)_{j,t-3}$	-3.1606	-3.1830	-3.2338	-3.2494	-4.1182
	(3.4498)	(3.4488)	(3.4580)	(3.4547)	(4.3217)
$Profitability_{j,t-3}$	0.7464	0.7497	0.7412	0.7418	0.7177
	(0.4706)	(0.4710)	(0.4714)	(0.4705)	(0.5652)
Peer Firm FE	+	+	+	+	
Year FE	+	+	+	+	+
Firm-Pair FE					+
Obs.	11,602,380	11,602,380	11,602,380	11,602,380	11,602,380
Adj. R^2 (%)	0.15	0.15	0.15	0.15	0.16

Table 3: Social Ties, Job Flows, and Non-compete Enforceability

This table presents the regression results examining how variations in state-level non-compete clause enforceability moderate the effects of social ties and job flows on pairwise citations. The dependent variable, $\ln(CiteNum_{i,m,j,n,t})$, is the logarithm of the number of times the patents produced by the focal firm i in county m and year t cite the patents produced by the peer firm j in county n and year $t-3$. $TreatedPost_{i,t}$ equals one if the focal firm's state has had a court ruling increasing non-compete enforceability before year t, and zero otherwise. $TreatedPost_{j,t}$ is similarly defined for the peer firm. $SCIShare_{m,n}$ and $JobFlow_{i,m,j,n,t-3}$ are defined as in Table 2. Standard errors (in parentheses) are clustered by firm-pair and year. Coefficients and standard errors are multiplied by 10^4. $^*p<.1$; $^{**}p<.05$; $^{***}p<.01$.

	Dependent Variable: $\ln(CiteNum_{i,m,j,n,t})$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$JobFlow_{i,m,j,n,t-3} \times TreatedPost_{j,t-3}$	-0.1698***		-0.1659***				-0.1302**
	(0.0577)		(0.0577)				(0.0512)
$JobFlow_{i,m,j,n,t-3} \times TreatedPost_{i,t-3}$		-0.1030***	-0.0916***				-0.0777**
		(0.0318)	(0.0303)				(0.0289)
$SCIShare_{m,n} \times TreatedPost_{j,t-3}$				-0.1776***		-0.1736**	-0.1436**
				(0.0621)		(0.0612)	(0.0558)
$SCIShare_{m,n} \times TreatedPost_{i,t-3}$					-0.0862**	-0.0763**	-0.0613*
					(0.0372)	(0.0342)	(0.0335)
$JobFlow_{i,m,j,n,t-3}$	0.1511***	0.1391***	0.1583***	0.1341***	0.1304***	0.1340***	0.1524***
	(0.0418)	(0.0376)	(0.0425)	(0.0376)	(0.0364)	(0.0376)	(0.0413)
$SCIShare_{m,n}$	0.2185***	0.2192***	0.2182***	0.2414***	0.2275***	0.2480***	0.2424***
	(0.0474)	(0.0473)	(0.0475)	(0.0508)	(0.0489)	(0.0521)	(0.0518)
$TreatedPost_{j,t-3}$	0.4678*		0.4468*		0.4320	0.4071	0.9728**
	(0.2434)		(0.2420)		(0.2697)	(0.2651)	(0.3737)
$TreatedPost_{i,t-3}$		0.2719		0.2053	0.1758	0.1166	0.4502
		(0.2185)		(0.2156)	(0.2357)	(0.2255)	(0.2890)
$\ln(Distance_{m,n}^{-1})$	0.3967***	0.3841***	0.3933***	0.4008***	0.3854***	0.3984***	0.4025***
	(0.0919)	(0.0920)	(0.0917)	(0.0924)	(0.0925)	(0.0927)	(0.0925)
Controls	+	+	+	+	+	+	+
Focal Firm FE	+	+	+	+	+	+	+
Year FE	+	+	+	+	+	+	+
Obs.	11,602,380	11,602,380	11,602,380	11,602,380	11,602,380	11,602,380	11,602,380
Adj. R^2 (%)	0.15	0.15	0.15	0.15	0.15	0.15	0.15

Table 4: Social Ties, Job Flows, and Disruptive Technologies

This table presents the regression results examining how disruptive technologies affect innovation spillovers through social ties and job flows. The dependent variable, $\ln(CiteNum_{i,m,j,n,t})$, is the logarithm of the number of times the patents produced by the focal firm i in county m and year t cite the patents produced by the peer firm j in county n and year $t-3$. $Disruptive_{j,t-3}$ equals one if the peer firm filed a patent in disruptive technology in year $t-3$. $Pioneer_{j,t-3}$ equals one if the peer firm's patent filed in year $t-3$ is a pioneer patent in its disruptive technology category. $SCIShare_{m,n}$ and $JobFlow_{i,m,j,n,t-3}$ are defined as in Table 2. Standard errors (in parentheses) are clustered by firm-pair and year. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

	Dependent Variable: $\ln(CiteNum_{i,m,j,n,t})$					
	(1)	(2)	(3)	(4)	(5)	(6)
$SCIShare_{m,n} \times Disruptive_{j,t-3}$	0.2500**				0.1216	
	(0.0916)				(0.1044)	
$SCIShare_{m,n} \times Pioneer_{j,t-3}$		0.3052**				0.1799
		(0.1083)				(0.1218)
$JobFlow_{i,m,j,n,t-3} \times Disruptive_{j,t-3}$			0.5279***		0.5007***	
			(0.1614)		(0.1684)	
$JobFlow_{i,m,j,n,t-3} \times Pioneer_{j,t-3}$				0.5437**		0.5076**
				(0.1929)		(0.1999)
$SCIShare_{m,n}$	0.1303***	0.1280***	0.2250***	0.2046***	0.1778***	0.1596***
	(0.0332)	(0.0318)	(0.0507)	(0.0459)	(0.0371)	(0.0347)
$JobFlow_{i,m,j,n,t-3}$	0.1725***	0.1629***	-0.0449	0.0110	-0.0345	0.0206
	(0.0478)	(0.0466)	(0.0309)	(0.0300)	(0.0343)	(0.0320)
Controls	+	+	+	+	+	+
Focal Firm FE	+	+	+	+	+	+
Peer Firm FE	+	+	+	+	+	+
Year FE	+	+	+	+	+	+
Obs.	7,324,534	7,324,534	7,324,534	7,324,534	7,324,534	7,324,534
Adj. R^2 (%)	0.30	0.30	0.30	0.30	0.30	0.30

Table 5: Social Ties, Job Flows, and Firm Innovation

This table presents panel regression results of peer innovation measures and focal firm innovation. In panel A, the dependent variable, $ln(FocalCiteNum_{i,m,t})$, is the logarithm of focal firm i's number of citations in county m year t to patents filed by peer firms in year $t-3$. In panel B, the dependent variable, $ln(FocalPat_{i,m,t})$, is the logarithm of focal firm i's citation-weighted number of patents filed in county m year t. $SpatialPeer_Pat_{im,t-3}$ is the inverse-distance-weighted number of peer patents in year $t-3$. $SocialPeer_Pat_{im,t-3}$ is the SCI-weighted number of peer patents in year $t-3$. $JobFlowPeer_Pat_{im,t-3}$ is the job-to-job transition probability (across industries and states) weighted number of peer patents in year $t-3$. Firm controls include firm size, book leverage, fixed assets, R&D intensity, profitability, and federal and state-induced R&D user cost. We also control for year, state, and firm fixed effects. Refer to Appendix Table A.1 for detailed variable definitions. Standard errors (in parentheses) are clustered at the 3-digit SIC by year level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A: Knowledge Spillovers– Direct Effect					
Dependent Variable	$ln(FocalCiteNum_{i,m,t})$				
	(1)	(2)	(3)	(4)	(5)
$SpatialPeer_Pat_{im,t-3}$	0.0775***			-0.0459***	-0.0402***
	(0.0074)			(0.0101)	(0.0117)
$SocialPeer_Pat_{im,t-3}$		0.0849***		0.1081***	0.0988***
		(0.0061)		(0.0078)	(0.0095)
$JobFlowPeer_Pat_{im,t-3}$			0.1069***	0.0727***	0.0891***
			(0.0047)	(0.0041)	(0.0056)
Firm Controls	+	+	+	+	+
Year FE	+	+	+	+	+
Firm FE	+	+	+	+	+
Own State FE					+
Obs.	270,694	270,694	270,694	270,694	270,694
Adj. R^2 (%)	7.1	7.2	7.7	7.8	8.0

Panel B: Knowledge Spillovers–Total Effect					
Dependent Variable	$ln(FocalPat_{i,m,t})$				
	(1)	(2)	(3)	(4)	(5)
$SpatialPeer_Pat_{im,t-3}$	0.1202***			-0.0570***	-0.0316***
	(0.0087)			(0.0102)	(0.0111)
$SocialPeer_Pat_{im,t-3}$		0.1292***		0.1570***	0.1241***
		(0.0070)		(0.0074)	(0.0096)
$JobFlowPeer_Pat_{im,t-3}$			0.1518***	0.0964***	0.1184***
			(0.0042)	(0.0035)	(0.0049)
Firm Controls	+	+	+	+	+
Year FE	+	+	+	+	+
Firm FE	+	+	+	+	+
Own State FE					+
Adj. R^2 (%)	0.1107	0.1138	0.1232	0.1236	0.1285
Obs.	270,694	270,694	270,694	270,694	270,694

Table 6: Predicting Firm Innovation Using R&D Tax Credits

This table presents the validity test of the IV strategy by examining how a higher R&D user cost affects firm innovation. The dependent variable, $ln(Pat_{im,t})$, is the logarithm of firm $i's$ number of patents filed in county m year t. *R&D User Cost*$^{State}_{im,t-3}$ and *R&D User Cost*$^{Federal}_{im,t-3}$ are the R&D user cost for firm i located in county m in year $t-3$, induced by the state and federal tax credits, respectively. Firm controls include firm size, book leverage, fixed assets, R&D intensity, and profitability. We also control for year, state, and firm fixed effects. Refer to Appendix Table A.1 for detailed variable definitions. Standard errors (in parentheses) are clustered at the 3-digit SIC by year level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Dependent Variable	$ln(Pat_{im,t})$	
	(1)	(2)
R&D User Cost$^{State}_{im,t-3}$	-1.2745**	-1.2772**
	(0.4821)	(0.4821)
R&D User Cost$^{Federal}_{im,t-3}$		0.0566
		(0.0488)
Firm Controls	+	+
Year FE	+	+
State FE	+	+
Firm FE	+	+
Obs.	270,694	270,694
Adj. R^2	13.3	13.3

Table 7: Social Ties, Job Flows, and Firm Innovation (IV Estimation)

This table presents the IV estimation of peer innovation measures and focal firm innovation. In panel A, the dependent variable, $ln(FocalCiteNum_{i,m,t})$, is the logarithm of focal firm i's number of citations in county m year t to patents filed by peer firms in year $t-3$. In panel B, the dependent variable, $ln(FocalPat_{i,m,t})$, is the logarithm of focal firm i's citation-weighted number of patents filed in county m year t. $SpatialPeer_Pat_{im,t-3}$ is the inverse-distance-weighted number of peer patents in year $t-3$. $SocialPeer_Pat_{im,t-3}$ is the SCI-weighted number of peer patents in year $t-3$. $JobFlowPeer_Pat_{im,t-3}$ is the job-to-job transition probability (across industries and states) weighted number of peer patents in year $t-3$. Firm controls include firm size, book leverage, fixed assets, R&D intensity, profitability, and federal and state-induced R&D user cost. We also control for year, state, and firm fixed effects. Refer to Appendix Table A.1 for detailed variable definitions. Standard errors (in parentheses) are clustered at the 3-digit SIC by year level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A: Knowledge Spillovers– Direct Effect					
Dependent Variable	$ln(FocalCiteNum_{i,m,t})$				
	(1)	(2)	(3)	(4)	(5)
$SpatialPeer_Pat_{im,t-3}$	0.1459***			0.0698***	0.1127***
	(0.0114)			(0.0136)	(0.0210)
$SocialPeer_Pat_{im,t-3}$		0.1525***		0.0933***	0.0749***
		(0.0100)		(0.0116)	(0.0176)
$JobFlowPeer_Pat_{im,t-3}$			0.1574***	0.0797***	0.1208***
			(0.0057)	(0.0050)	(0.0076)
Firm Controls	+	+	+	+	+
Year FE	+	+	+	+	+
Firm FE	+	+	+	+	+
Own State FE					+
F-stats	5.1e+04	1.2e+05	2.9e+05	2.2e+04	1.8e+04
Obs.	185,941	185,941	185,941	185,941	185,941

Panel B: Knowledge Spillovers–Total Effect					
Dependent Variable	$ln(FocalPat_{i,m,t})$				
	(1)	(2)	(3)	(4)	(5)
$SpatialPeer_Pat_{im,t-3}$	0.1711***			0.0559***	0.1251***
	(0.0129)			(0.0124)	(0.0207)
$SocialPeer_Pat_{im,t-3}$		0.1912***		0.1363***	0.0838***
		(0.0110)		(0.0092)	(0.0168)
$JobFlowPeer_Pat_{im,t-3}$			0.1925***	0.0987***	0.1519***
			(0.0058)	(0.0050)	(0.0076)
Firm Controls	+	+	+	+	+
Year FE	+	+	+	+	+
Firm FE	+	+	+	+	+
Own State FE					+
F-stats	5.1e+04	1.2e+05	2.9e+05	2.2e+04	1.8e+04
Obs.	185,941	185,941	185,941	185,941	185,941

Table 8: Social Ties, Job Flows, and Firm Innovation:
Heterogeneous Effects Depending on Focal County's Characteristics

This table presents the heterogeneous effects of social ties and job flows in facilitating knowledge spillovers, depending on focal county characteristics. In panel A, the dependent variable, $ln(FocalCiteNum_{i,m,t})$, is the logarithm of focal firm i's number of citations in county m year t to patents filed by peer firms in year $t-3$. In panel B, the dependent variable, $ln(FocalPat_{i,m,t})$, is the logarithm of focal firm i's citation-weighted number of patents filed in county m year t. $SpatialPeer_Pat_{im,t-3}$ is the inverse-distance-weighted number of peer patents in year $t-3$. $SocialPeer_Pat_{im,t-3}$ is the SCI-weighted number of peer patents in year $t-3$. $JobFlowPeer_Pat_{im,t-3}$ is the job-to-job transition probability (across industries and states) weighted number of peer patents in year $t-3$. We explore five focal county characteristics: 1) the ratio of the local tech workers ($LocalTechWorkers$), 2) median income ($Income$), 3) average years of schooling ($Education$), 4) the ratio of people above 25 and below 60 ($WorkingPop$) and 5) economic connectedness (EC). *FocalCounty* is a dummy variable that takes a value of one if the focal county's corresponding characteristic is above the sample median in year $t-3$, and zero otherwise. Firm controls include firm size, book leverage, fixed assets, R&D intensity, profitability, and federal and state-induced R&D user cost. We also control for year, state, and firm fixed effects. Refer to Appendix Table A.1 for detailed variable definitions. Standard errors (in parentheses) are clustered at the 3-digit SIC by year level. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Panel A: Knowledge Spillovers– Direct Effect					
Dependent Variable	$ln(FocalCiteNum_{i,m,t})$				
			IV		
County Characteristics =	High LocalTechWorkers	High Income	High Education	High WorkingPop	High EC
$SpatialPeer_Pat_{im,t-3}$	0.0342*	0.1095***	0.1006***	0.0768***	0.1168***
	(0.0184)	(0.0206)	(0.0208)	(0.0197)	(0.0214)
$SocialPeer_Pat_{im,t-3}$	0.1145***	0.0309	-0.0346*	0.0118	-0.0151
	(0.0150)	(0.0255)	(0.0190)	(0.0174)	(0.0179)
$SocialPeer_Pat_{im,t-3} \times FocalCounty$	0.1326***	0.0588**	0.1200***	0.1018***	0.0995***
	(0.0134)	(0.0257)	(0.0096)	(0.0120)	(0.0082)
$JobFlowPeer_Pat_{im,t-3}$	0.0767***	0.0379	0.0967***	0.0580***	0.1031***
	(0.0072)	(0.0233)	(0.0129)	(0.0099)	(0.0104)
$JobFlowPeer_Pat_{im,t-3} \times FocalCounty$	0.1404***	0.1238***	0.1076***	0.1074***	0.0577***
	(0.0127)	(0.0297)	(0.0061)	(0.0112)	(0.0099)
FocalCounty Dummy	0.0431***	0.0123	0.1076***	0.0625***	0.0599***
	(0.0085)	(0.0116)	(0.0061)	(0.0057)	(0.0050)
Firm Controls	+	+	+	+	+
Year FE	+	+	+	+	+
Firm FE	+	+	+	+	+
Own State FE	+	+	+	+	+
F-stats	1.1e+04	2191.115	1.1e+04	7062.215	1.1e+04
Obs.	185,852	185,852	185,852	185,852	185,273

Panel B: Knowledge Spillovers–Total Effect					
Dependent Variable	$ln(FocalPat_{i,m,t})$				
	IV				
County Characteristics =	High LocalTechWorkers	High Income	High Education	High WorkingPop	High EC
$SpatialPeer_Pat_{im,t-3}$	0.0292	0.1238***	0.1171***	0.0756***	0.1275***
	(0.0179)	(0.0211)	(0.0205)	(0.0178)	(0.0217)
$SocialPeer_Pat_{im,t-3}$	0.1305***	0.0197	-0.0376**	-0.0088	-0.0265
	(0.0142)	(0.0310)	(0.0171)	(0.0160)	(0.0176)
$SocialPeer_Pat_{im,t-3} \times FocalCounty$	0.1676***	0.0813**	0.1233***	0.1460***	0.1259***
	(0.0136)	(0.0343)	(0.0086)	(0.0113)	(0.0083)
$JobFlowPeer_Pat_{im,t-3}$	0.1016***	0.0129	0.1275***	0.0905***	0.1375***
	(0.0071)	(0.0231)	(0.0104)	(0.0089)	(0.0088)
$JobFlowPeer_Pat_{im,t-3} \times FocalCounty$	0.1586***	0.2054***	0.0692***	0.1116***	0.0588***
	(0.0103)	(0.0301)	(0.0091)	(0.0104)	(0.0083)
FocalCounty Dummy	0.0668***	0.0275**	0.1630***	0.1018***	0.0743***
	(0.0094)	(0.0133)	(0.0065)	(0.0067)	(0.0053)
Firm Controls	+	+	+	+	+
Year FE	+	+	+	+	+
Firm FE	+	+	+	+	+
Own State FE	+	+	+	+	+
F-stats	1.1e+04	2191.115	1.1e+04	7062.215	1.1e+04
Obs.	185,852	185,852	185,852	185,852	185,273

A Appendix

Table A.1: Variable Definitions

Variable Name	Definition
$SCI_{m,n}$	Total number of friendship links between county m and county n, normalized relative to Los Angeles. It has a minimum value of zero and a maximum value of 1,000,000.
$SpatialPeer_Pat_{im,t}$	Inverse-distance-weighted peer innovations filed in year t by all peers of focal firm i in county m. Peer innovations are the number of patent counts. The measure is in the natural logarithm.
$SocialPeer_Pat_{im,t}$	The SCI-weighted peer innovations filed in year t by all peers of focal firm i in county m. Peer innovations are the number of patent counts. The measure is in the natural logarithm.
$JobFlowPeer_Pat_{im,t}$	The job-to-job transition probability weighted peer innovations filed in year t by all peers of focal firm i in county m. Peer innovations are the number of patent counts. The measure is in the natural logarithm.
$ProdPeer_Pat_{im,t}$	Production network weighted peer innovations filed in year t by all peers of focal firm i in county m. The production network is obtained from the Compustat supplier-customer link, based on which we calculate the sales share of a supplier in the customer's overall portfolio. Peer innovations are the number of patent counts. The measure is in the natural logarithm.
$TechPeer_Pat_{im,t}$	Technology similarity weighted peer innovations filed in year t by all peers of focal firm i in county m. The technology similarity measure is obtained from Lee et al. (2019), which calculates the overlap of firm pair-wise patenting probabilities in each technology class and spans from 2000 to 2010. Peer innovations are the number of patent counts. The measure is in the natural logarithm.
$ln(FocalCiteNum_{i,m,t})$	The natural logarithm of focal firm i's number of citations in county m year t to patents filed by peer firms in year $t-3$.
$ln(FocalPat_{i,m,t})$	The natural logarithm of focal firm i's citation-weighted number of patents filed in county m year t.
$ln(FirmSize)_{i,t}$	The logarithm of firm i's total assets at the end of year t.
$BookLeverage_{i,t}$	The proportion of total liabilities to total book value for firm i in year t.
$ln(FixedAssets)_{i,t}$	The logarithm of firm i's fixed assets at the end of year t.
$R\&DIntensity_{i,t}$	The ratio of R&D expenditures to sales for firm i in year t.
$Profitability_{i,t}$	Firm i's return on asset (ROA) in year t.
$R\&DUserCost^{State}_{im,t}$	Firm i's specific user cost of R&D activities induced by the state-level R&D tax credits for its R&D location in county m year t. This measure is calculated based on Lucking et al. (2018).
$R\&DUserCost^{Fed}_{i,t}$	Firm i's specific user cost of R&D activities induced by the federal level R&D tax credits in year t. This measure is calculated based on Lucking et al. (2018).
$LocalTechWorkers_{m,t}$	Annual estimates of focal county $m's$ share of local tech workers out of all workers.
$Income_{m,t}$	Annual estimates of focal county $m's$ median dollar income.
$YearsOfSchooling_{m,t}$	Annual estimates of the average years of schooling in county m.
$WorkingPop_{m,t}$	Annual estimates of the share of populations that are at their working age, i.e., from 25 to 60, in county m.
$EconomicConnectedness_{m,t}$	The degree of interaction between individuals from low- and high-income groups based on anonymized friendship links from Facebook. This measure is directly obtained from Chetty et al. (2022a).

Table A.2: Social Ties, Job Flows, and Pairwise Citations: Poisson Regressions

This table presents the Poisson regression results of pairwise citations on social ties and job flows. The dependent variable, $CiteNum_{i,m,j,n,t}$, is the number of times the patents produced by the focal firm i in county m and year t cite the patents produced by the peer firm j in county n and year $t-3$. $SCIShare_{m,n}$ is the SCI share between a focal county m and a friend county n, calculated as $\frac{SCI_{m,n}}{\sum_n SCI_{m,n}}$. $JobFlow_{i,m,j,n,t-3}$ is the job transition probability between focal firm i's two-digit NAICS industry in county m's state and peer firm j's two-digit NAICS industry in county n's state. Decile ranks of $SCIShare_{m,n}$ and $JobFlow_{i,m,j,n,t-3}$ are used in the regression. Standard errors (in parentheses) are clustered by firm-pair and year. Coefficients and standard errors are multiplied by 10^4. $^*p<.1$; $^{**}p<.05$; $^{***}p<.01$.

	Dependent Variable: $CiteNum_{i,m,j,n,t}$				
	(1)	(2)	(3)	(4)	(5)
$\ln(Distance_{i,j}^{-1})$	0.0529			0.3619***	0.3684***
	(0.0963)			(0.0492)	(0.0532)
$SCIShare_{m,n}$		0.2404***		0.2274***	0.2296***
		(0.0292)		(0.0239)	(0.0244)
$JobFlow_{i,m,j,n,t-3}$			0.1493***	0.1377***	0.1360***
			(0.0429)	(0.0467)	(0.0474)
$RDIntensity_{i,t}$	-6.5292***	-6.3622***	-6.5076***	-6.2635***	-5.8737***
	(1.9376)	(1.9041)	(1.9344)	(1.8797)	(1.8541)
$\ln(FirmSize)_{i,t}$	-0.8566***	-0.8388***	-0.8530***	-0.8240***	-0.8689***
	(0.1671)	(0.1634)	(0.1657)	(0.1627)	(0.1696)
$BookLeverage_{i,t}$	2.0835***	2.0898***	2.0059**	2.0041**	2.0701**
	(0.8020)	(0.8082)	(0.7941)	(0.7905)	(0.8037)
$\ln(FixedAssets)_{i,t}$	-0.6878	-0.7834	-0.7406	-0.8544	-0.9773
	(1.3353)	(1.3091)	(1.3290)	(1.2949)	(1.4433)
$Profitability_{i,t}$	0.9462**	0.9376**	0.9164**	0.9118**	1.0000*
	(0.4183)	(0.4139)	(0.4179)	(0.4067)	(0.5288)
$RDIntensity_{j,t}$	2.9827***	2.9692***	2.8278***	2.7766**	2.0273
	(1.0985)	(1.1174)	(1.0728)	(1.0780)	(1.6246)
$\ln(FirmSize)_{j,t}$	0.2378	0.2324	0.2204	0.2037	0.1367
	(0.2107)	(0.2019)	(0.2095)	(0.1989)	(0.2227)
$BookLeverage_{j,t}$	-0.3304	-0.2943	-0.3173	-0.2625	0.2163
	(0.5484)	(0.5675)	(0.5676)	(0.5912)	(0.6995)
$\ln(FixedAssets)_{j,t}$	-2.0454	-2.4097	-2.1820	-2.5817	-2.6905
	(2.2968)	(2.4082)	(2.3773)	(2.4625)	(2.6250)
$Profitability_{j,t}$	-0.0123	-0.0524	-0.0720	-0.0825	-0.5966
	(0.4849)	(0.4873)	(0.4783)	(0.4777)	(0.5636)
Focal Firm FE	+	+	+	+	
Peer Firm FE	+	+	+	+	
Year FE	+	+	+	+	+
Firm-Pair FE					+
Obs.	5,415,770	5,415,770	5,415,770	5,415,770	1,916,260

Table A.3: Social Ties, Job Flows, and Firm Innovation: Controlling for Other Peer Networks

This table presents panel regression results of peer innovation measures and focal firm innovation, with peer production and technology networks as additional controls. In panel A, the dependent variable, $ln(FocalCiteNum_{i,m,t})$, is the logarithm of focal firm i's number of citations in county m year t to patents filed by peer firms in year $t-3$. In panel B, the dependent variable, $ln(FocalPat_{i,m,t})$, is the logarithm of focal firm i's citation-weighted number of patents filed in county m year t. $SpatialPeer_Pat_{im,t-3}$ is the inverse-distance-weighted number of peer patents in year $t-3$. $SocialPeer_Pat_{im,t-3}$ is the SCI-weighted number of peer patents in year $t-3$. $JobFlowPeer_Pat_{im,t-3}$ is the job-to-job transition probability (across industries and states) weighted number of peer patents in year $t-3$. $ProdPeer_Pat_{im,t-3}$ and $TechPeer_Pat_{im,t-3}$ are peer innovations weighted by Compustat supplier-customer link and firm pair-wise technology similarities, respectively. Firm controls include firm size, book leverage, fixed assets, R&D intensity, profitability, and federal and state-induced R&D user cost. We also control for year, state, and firm fixed effects. Refer to Appendix Table A.1 for detailed variable definitions. Standard errors (in parentheses) are clustered at the 3-digit SIC by year level. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Panel A: Knowledge Spillovers– Direct Effect

Dependent Variable	$ln(FocalCiteNum_{i,m,t})$				
	(1)	(2)	(3)	(4)	(5)
$SpatialPeer_Pat_{im,t-3}$	0.0635***			-0.0496***	-0.0395***
	(0.0084)			(0.0109)	(0.0123)
$SocialPeer_Pat_{im,t-3}$		0.0736***		0.1026***	0.0908***
		(0.0072)		(0.0094)	(0.0112)
$JobFlowPeer_Pat_{im,t-3}$			0.0913***	0.0589***	0.0827***
			(0.0055)	(0.0043)	(0.0067)
$ProdPeer_Pat_{im,t-3}$	0.0016	0.0017	0.0014	0.0017	0.0019
	(0.0082)	(0.0082)	(0.0082)	(0.0082)	(0.0082)
$TechPeer_Pat_{im,t-3}$	-0.0053	-0.0057	-0.0107**	-0.0082	-0.0112**
	(0.0056)	(0.0055)	(0.0053)	(0.0054)	(0.0053)
Firm Controls	+	+	+	+	+
Year FE	+	+	+	+	+
Firm FE	+	+	+	+	+
Own State FE					+
Obs.	167,686	167,686	167,686	167,686	167,686
Adj. R^2 (%)	7.8	7.9	8.4	8.4	8.7

Panel B: Knowledge Spillovers–Total Effect					
Dependent Variable	$ln(FocalPat_{i,m,t})$				
	(1)	(2)	(3)	(4)	(5)
$SpatialPeer_Pat_{im,t-3}$	0.1445***			-0.0533***	-0.0318**
	(0.0125)			(0.0136)	(0.0141)
$SocialPeer_Pat_{im,t-3}$		0.1532***		0.1802***	0.1545***
		(0.0093)		(0.0088)	(0.0121)
$JobFlowPeer_Pat_{im,t-3}$			0.1697***	0.0986***	0.1427***
			(0.0051)	(0.0038)	(0.0060)
$ProdPeer_Pat_{im,t-3}$	-0.0047	-0.0044	-0.0048	-0.0046	-0.0043
	(0.0042)	(0.0042)	(0.0043)	(0.0043)	(0.0044)
$TechPeer_Pat_{im,t-3}$	-0.0369***	-0.0361***	-0.0436***	-0.0416***	-0.0460***
	(0.0063)	(0.0061)	(0.0062)	(0.0063)	(0.0065)
Firm Controls	+	+	+	+	+
Year FE	+	+	+	+	+
Firm FE	+	+	+	+	+
Own State FE					+
Obs.	167,686	167,686	167,686	167,686	167,686
Adj. R^2 (%)	12.6	13.0	13.9	13.9	14.7

Table A.4: Social Ties, Job Flows, and Firm Innovation: Controlling for Other Peer Networks (IV Estimation)

This table presents the IV estimation of peer innovation measures and focal firm innovation, with peer production and technology networks as additional controls. In panel A, the dependent variable, $ln(FocalCiteNum_{i,m,t})$, is the logarithm of focal firm i's number of citations in county m year t to patents filed by peer firms in year $t-3$. In panel B, the dependent variable, $ln(FocalPat_{i,m,t})$, is the logarithm of focal firm i's citation-weighted number of patents filed in county m year t. $SpatialPeer_Pat_{im,t-3}$ is the inverse-distance-weighted number of peer patents in year $t-3$. $SocialPeer_Pat_{im,t-3}$ is the SCI-weighted number of peer patents in year $t-3$. $JobFlowPeer_Pat_{im,t-3}$ is the job-to-job transition probability (across industries and states) weighted number of peer patents in year $t-3$. $ProdPeer_Pat_{im,t-3}$ and $TechPeer_Pat_{im,t-3}$ are peer innovations weighted by Compustat supplier-customer link and firm pair-wise technology similarities, respectively. Firm controls include firm size, book leverage, fixed assets, R&D intensity, profitability, and federal and state-induced R&D user cost. We also control for year, state, and firm fixed effects. Refer to Appendix Table A.1 for detailed variable definitions. Standard errors (in parentheses) are clustered at the 3-digit SIC by year level. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Panel A: Knowledge Spillovers– Direct Effect (IV)

Dependent Variable	$ln(FocalCiteNum_{i,m,t})$				
	(1)	(2)	(3)	(4)	(5)
$SpatialPeer_Pat_{im,t-3}$	0.1412***			0.0652***	0.1227***
	(0.0159)			(0.0177)	(0.0297)
$SocialPeer_Pat_{im,t-3}$		0.1565***		0.1067***	0.0790***
		(0.0140)		(0.0168)	(0.0265)
$JobFlowPeer_Pat_{im,t-3}$			0.1513***	0.0717***	0.1333***
			(0.0077)	(0.0057)	(0.0108)
$ProdPeer_Pat_{im,t-3}$	0.0771	0.0758	0.0818*	0.0714	0.0800*
	(0.0476)	(0.0476)	(0.0464)	(0.0472)	(0.0473)
$TechPeer_Pat_{im,t-3}$	-0.2104**	-0.1779**	-0.1466*	-0.1763**	-0.1942**
	(0.0971)	(0.0868)	(0.0775)	(0.0839)	(0.0876)
Firm Controls	+	+	+	+	+
Year FE	+	+	+	+	+
Firm FE	+	+	+	+	+
Own State FE					+
F-stats	352.984	353.487	351.340	213.583	211.940
Obs.	98,044	98,044	98,044	98,044	98,044

Panel B: Knowledge Spillovers–Total Effect (IV)					
Dependent Variable	$ln(FocalPat_{i,m,t})$				
	(1)	(2)	(3)	(4)	(5)
$SpatialPeer_Pat_{im,t-3}$	0.2082***			0.0746***	0.1279***
	(0.0189)			(0.0177)	(0.0338)
$SocialPeer_Pat_{im,t-3}$		0.2335***		0.1703***	0.1318***
		(0.0139)		(0.0141)	(0.0268)
$JobFlowPeer_Pat_{im,t-3}$			0.2199***	0.1051***	0.2076***
			(0.0074)	(0.0060)	(0.0090)
$ProdPeer_Pat_{im,t-3}$	0.0944**	0.0938**	0.1029**	0.0952**	0.1124**
	(0.0429)	(0.0427)	(0.0419)	(0.0416)	(0.0441)
$TechPeer_Pat_{im,t-3}$	-0.2762**	-0.2473**	-0.1906**	-0.2432***	-0.2479***
	(0.1080)	(0.0987)	(0.0779)	(0.0923)	(0.0933)
Firm Controls	+	+	+	+	+
Year FE	+	+	+	+	+
Firm FE	+	+	+	+	+
Own State FE					+
F-stats	352.984	353.487	351.340	213.583	211.940
Obs.	98,044	98,044	98,044	98,044	98,044

Table A.5: Social Ties, Job Flows, and Firm Innovation: Out of State Peer Networks

This table presents the panel regression results of peer innovation measures and focal firm innovation, with only out-of-state social ties and job flow-based peer innovations. In panel A, the dependent variable, $ln(FocalCiteNum_{i,m,t})$, is the logarithm of focal firm i's number of citations in county m year t to patents filed by peer firms in year $t-3$. In panel B, the dependent variable, $ln(FocalPat_{i,m,t})$, is the logarithm of focal firm i's citation-weighted number of patents filed in county m year t. $SpatialPeer_Pat_{im,t-3}$ is the inverse-distance-weighted number of peer patents in year $t-3$. $SocialPeer_Pat_{im,t-3}^{OutState}$ is the SCI-weighted number of out-of-state peer patents in year $t-3$. $JobFlowPeer_Pat_{im,t-3}^{OutState}$ is the job-to-job transition probability (across industries and states) weighted number of out-of-state peer patents in year $t-3$. Firm controls include firm size, book leverage, fixed assets, R&D intensity, profitability, and federal and state-induced R&D user cost. We also control for year, state, and firm fixed effects. Refer to Appendix Table A.1 for detailed variable definitions. Standard errors (in parentheses) are clustered at the 3-digit SIC by year level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A: Knowledge Spillovers– Direct Effect					
Dependent Variable	$ln(FocalCiteNum_{i,m,t})$				
	(1)	(2)	(3)	(4)	(5)
$SpatialPeer_Pat_{im,t-3}$	0.0775***			0.0285***	0.0068
	(0.0074)			(0.0095)	(0.0099)
$SocialPeer_Pat_{im,t-3}^{OutState}$		0.0153***		0.0467***	0.0392***
		(0.0044)		(0.0030)	(0.0036)
$JobFlowPeer_Pat_{im,t-3}^{OutState}$			0.1081***	0.0923***	0.0986***
			(0.0055)	(0.0068)	(0.0078)
Firm Controls	+	+	+	+	+
Year FE	+	+	+	+	+
Firm FE	+	+	+	+	+
Own State FE					+
Obs.	270,694	270,694	270,694	270,694	270,694
Adj. R^2 (%)	7.1	6.8	7.5	7.7	7.9

Panel B: Knowledge Spillovers–Total Effect					
Dependent Variable	$ln(FocalPat_{i,m,t})$				
	(1)	(2)	(3)	(4)	(5)
$SpatialPeer_Pat_{im,t-3}$	0.1202***			0.0580***	0.0258**
	(0.0087)			(0.0113)	(0.0114)
$SocialPeer_Pat^{OutState}_{im,t-3}$		0.0389***		0.0694***	0.0543***
		(0.0046)		(0.0028)	(0.0033)
$JobFlowPeer_Pat^{OutState}_{im,t-3}$			0.1481***	0.1182***	0.1282***
			(0.0060)	(0.0070)	(0.0080)
Firm Controls	+	+	+	+	+
Year FE	+	+	+	+	+
Firm FE	+	+	+	+	+
Own State FE					+
Obs.	270,694	270,694	270,694	270,694	270,694
Adj. R^2 (%)	11.1	10.5	11.7	12.1	12.7

Table A.6: Social Ties, Job Flows, and Firm Innovation: Out of State Peer Networks (IV Estimation)

This table presents the IV estimation of peer innovation measures and focal firm innovation, with only out-of-state social ties and job flow-based peer innovations. In panel A, the dependent variable, $ln(FocalCiteNum_{i,m,t})$, is the logarithm of focal firm i's number of citations in county m year t to patents filed by peer firms in year $t-3$. In panel B, the dependent variable, $ln(FocalPat_{i,m,t})$, is the logarithm of focal firm i's citation-weighted number of patents filed in county m year t. $SpatialPeer_Pat_{im,t-3}$ is the inverse-distance-weighted number of peer patents in year $t-3$. $SocialPeer_Pat_{im,t-3}^{OutState}$ is the SCI-weighted number of out-of-state peer patents in year $t-3$. $JobFlowPeer_Pat_{im,t-3}^{OutState}$ is the job-to-job transition probability (across industries and states) weighted number of out-of-state peer patents in year $t-3$. Firm controls include firm size, book leverage, fixed assets, R&D intensity, profitability, and federal and state-induced R&D user cost. We also control for year, state, and firm fixed effects. Refer to Appendix Table A.1 for detailed variable definitions. Standard errors (in parentheses) are clustered at the 3-digit SIC by year level. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Panel A: Knowledge Spillovers– Direct Effect (IV)					
Dependent Variable	$ln(FocalCiteNum_{i,m,t})$				
	(1)	(2)	(3)	(4)	(5)
$SpatialPeer_Pat_{im,t-3}$	0.1459***			0.1301***	0.1097***
	(0.0114)			(0.0160)	(0.0154)
$SocialPeer_Pat_{im,t-3}^{OutState}$		0.0179**		0.0830***	0.0653***
		(0.0085)		(0.0116)	(0.0093)
$JobFlowPeer_Pat_{im,t-3}^{OutState}$			0.2030***	0.1343***	0.1752***
			(0.0108)	(0.0120)	(0.0164)
Firm Controls	+	+	+	+	+
Year FE	+	+	+	+	+
Firm FE	+	+	+	+	+
Own State FE					+
F-stats	5.1e+04	4.1e+04	1.4e+05	2514.184	5723.972
Obs.	185,941	185,941	185,941	185,941	185,941

Panel B: Knowledge Spillovers–Total Effect (IV)					
Dependent Variable	$ln(FocalPat_{i,m,t})$				
	(1)	(2)	(3)	(4)	(5)
$SpatialPeer_Pat_{im,t-3}$	0.1711***			0.1057***	0.1136***
	(0.0129)			(0.0193)	(0.0158)
$SocialPeer_Pat_{im,t-3}^{OutState}$		0.0084		0.0510***	0.0437***
		(0.0079)		(0.0129)	(0.0101)
$JobFlowPeer_Pat_{im,t-3}^{OutState}$			0.2283***	0.1737***	0.1948***
			(0.0115)	(0.0132)	(0.0155)
Firm Controls	+	+	+	+	+
Year FE	+	+	+	+	+
Firm FE	+	+	+	+	+
Own State FE					+
F-stats	5.1e+04	4.1e+04	1.4e+05	2514.184	5723.972
Obs.	185,941	185,941	185,941	185,941	185,941