

Are Cross-Regional Collaborations Good for Local R&D?

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ABSTRACT

R&D activities are increasingly conducted by researchers from different geographic locations. Such collaborations should promote knowledge flow across distance and benefit local R&D communities. However, the nature of cross-regional collaborations varies widely across organizational contexts. Compared with collaborations within entrepreneurial firms, those within large organizations tend to be highly structured, which reduces the need for interpersonal interaction and increases internal interdependence, thus hindering communications beyond firm boundaries. Examining the global pharmaceutical industry from 1975 to 2001, we find that cross-regional ties in big pharma companies contribute significantly less to local innovation than those initiated by their smaller counterparts, and the pattern persists over time.

1. Introduction

In January 2004, the Swiss pharmaceutical giant Roche announced the opening of its fifth global pharmaceutical R&D center in Shanghai, China. The entry of Roche in the area is expected to generate significant knowledge spillover to the local community. Meanwhile, the company emphasized that “the new center will be part of Roche’s global pharmaceutical R&D network.” In particular, the local employees will be working with their counterparts in Penzberg, Germany on anti-cancer drugs; in Palo Alto, California on anti-HIV agents; in Nutley, New Jersey on drugs for obesity treatment, and in Basel, Switzerland on therapies for Alzheimer’s disease. How will such cross-regional collaborations affect the expected knowledge spillover to local firms?

From a network perspective, interpersonal collaboration proves an effective means of knowledge transfer (Cockburn and Henderson, 1998, Singh 2005a). Through frequent interactions and joint problem solving (McEvily and Marcus 2005), geographically separated team members gain access to tacit

knowledge bounded at distant locations (Jaffe *et al.* 1993, Audretsch and Feldman 1996, Furman *et al.* 2004), and thus bring fresh perspectives to innovators in the local R&D community.

However, the answer may be very different once we consider cross-regional collaborations in the context of firm organization. First, in established organizations, reliance on formal structures and operational routines reduces the need for extensive interpersonal exchanges (Scott and Davis 2006: 38-40), a crucial mechanism of knowledge transfer. Second, as researchers assume specific roles in a collaborative relationship, their understanding of the overall technological architecture may be fragmentary, which makes it difficult for them to convey knowledge effectively to others outside the organization (Rajan and Zingales 2001).

Despite the large literatures on team collaborations and on organizational heterogeneity, the interaction between these two is still understudied. This paper aims to integrate these two perspectives by examining the specific case of cross-regional collaborations in R&D. We hypothesize that the effect of cross-regional collaborations varies widely, depending on the organizational contexts within which the collaborations are embedded. While network connections with other locations are beneficial to local R&D in general, those organized in large, established organizations entail less interpersonal interaction – hence less knowledge transfer across distance – but higher technological interdependence among the firms' geographically dispersed units, which engenders higher barriers to cross-organizational learning.

We test the hypothesis with pharmaceutical industry data from 1975 to 2001. In this period, the birth of contemporary technologies created “a burst of new companies” (Chandler 2005). Meanwhile, the rapid development of information technologies has made it easier for researchers to access distant knowledge and engage in cross-regional collaborations. Such environments offer an opportunity for us to assess the roles of firm organization and collaborative interactions.

Our empirical results show that cross-regional collaborations play an important role in bridging locally clustered R&D activities. Such collaborations not only increase the value of innovations directly resulting from the collaborations, but also benefit local R&D in general. However, the contribution of cross-regional collaborations formed by the largest pharmaceutical companies is found to be significantly

lower than that of similar collaborations formed by small ventures, and the gap remains large over time. The findings are further corroborated by interviews in the Zhangjiang Hi-Tech Park of Shanghai, China. Interestingly, local researchers reported helpful communications with the “well-connected” but “simple” firms in the community, but felt “left out” by the “isolated islands,” – global R&D operations set up by large multinational firms.

The rest of the paper is organized as follows. Section 2 develops the theoretical framework and the main hypotheses. Section 3 introduces the data sources and describes the empirical setup. The empirical results and robustness analyses are discussed in Sections 4 and 5, respectively. Section 6 concludes.

2. Theory Development

2.1 Localized Spillover and Cross-Regional Collaboration

Innovations are often the result of the combination and recombination of existing knowledge (Schumpeter 1939, Kogut and Zander 1992, Fleming 2001). In the pharmaceutical industry, for example, new drug development usually requires the input of scientists skilled in a wide range of disciplines (Henderson and Cockburn 1994). As R&D projects become larger and more complex, collaborations are increasingly indispensable (Arora and Gambardella 1994, Jones 2005). In fact, we find that the percentage of U.S. patents produced by teams of three or more inventors steadily increased from 16.4% in 1975 to 34.8% in 1995. For drug and medical patents, the percentages are 25.7% and 43.7%, respectively.

Meanwhile, different geographic regions remain specialized in different knowledge bases (Cantwell and Janne 1999, Verspagen and Schoenmakers 2004). For example, within the pharmaceutical industry, there is a concentration of biotechnology firms in Boston and cardiovascular equipment manufacturers in Minneapolis. Calculating the technological distance (Jaffe 1986) between each pair of metropolitan areas in the United States, based on both pharmaceutical patents and patents in all categories, we find little sign of technological convergence across regions in the past three decades.

With geographically bounded knowledge pools, scientists from different locations may find it beneficial to collaborate. Technology transfer has proven to be challenging even within the same firm

(Szulanski 1996). Teamwork and joint problem-solving facilitate the acquisition of tacit and complex knowledge by providing a forum for experimentation, observation, and search for solutions (McEvily and Marcus 2005). In that sense, interpersonal interactions help alleviate the difficulty of knowledge transfer across distance (Lahiri 2003, Frost and Zhou 2005, Singh, 2005b).

The effect of cross-regional collaborations, however, is not limited to the firms that initiate the collaborations. Such long-distance linkages also bring fresh perspectives and expand the horizon for all neighboring firms through localized knowledge spillover. Since firms are more likely to search for and apply knowledge close to their own technological positions (Cohen and Levinthal 1990, Podolny and Stuart 1995), collocation of similar firms can promote cross learning in the local community. However, too much localized connection may also prevent firms from identifying new trends or exploring novel ideas, partly due to the recirculation of redundant information (Uzzi and Spiro 2004). March (1991) argues that exploiting certainties at the expense of exploring new possibilities can be detrimental to a firm in the long run. A similar argument should also apply to geographic clusters: A region with little interaction with the outside world is less likely to remain dynamic and innovative. Hence, technologies emerging from cross-regional collaborations can be great sources of knowledge for local R&D.

2.2 Firm Organization and Knowledge Internalization

The phenomenon of cross-regional collaborations is interesting by itself, but we cannot fully understand the role of such collaborations without taking firm organization into consideration. Collaborations occur in various institutional contexts: among university scholars, entrepreneurial researchers, or scientists at large multinational organizations. Hence, the nature of knowledge transfer among the collaborators may well be shaped by the organizational structure they are embedded in.

In recent years, large established corporations have been playing an important role in the ever-increasing occurrences of cross-regional collaborations. Multinational firms have long been recognized for their capacity to assimilate, generate, and integrate knowledge on a global basis (Bartlett and Ghoshal 1990, Feinberg and Gupta 2004). Long-established institutions and internal deployment of employees

across subunits help facilitate collaborations that would not be possible otherwise. The development of information technologies further strengthens the coordination abilities of the multi-unit, multi-location firms and allows them to spread out their R&D activities worldwide (Alcácer *et al.* 2006).

Because of the complex organizational structures and processes that large firms have, their internal ties may not have the same spillover effect as those established by smaller firms. First, administrative routines in large organizations often take the place of extensive interaction among individuals, thus limiting the tacit knowledge transferred across distance. Second, highly structured collaborations increase the internal interdependence among local units. With a more firm-specific knowledge base, local employees may find it more difficult to communicate across firm boundaries. We elaborate the two key factors – less interaction and more interdependence – in the following two subsections.

2.2.1 Interpersonal Interaction

Extensive interpersonal interaction involved in R&D collaborations is cited as the main reason why collaborations promote the diffusion of intellectual capital (Zucker and Darby 2005). In entrepreneurial environments, due to the intangible nature and high uncertainty of R&D activities, any collaborative relationship between individuals essentially calls for mutual trust and deep appreciation for each other's work. Once the collaborative relationship is established, frequent interaction is necessary to maintain productivity. Because collaborations are less structured in such an environment, researchers often resort to experimentation and explorations to achieve the common goals (McEvily and Marcus 2005), which leads to comprehensive understanding of the issues they are facing.

During the interviews conducted for this study, many researchers working at small or median enterprises acknowledged that they collaborate extensively with their colleagues out of town, who are sometimes their former officemates or graduate school classmates. "We talk a lot, about literally everything, and we keep each other updated," one researcher remarked. "Sometimes we have to go through ten different topics before identifying the real problem and coming up with a solution."

This may not be the case in a more formal organizational structure, where the role of each

individual is well appointed and team members form “stable expectations” regarding the behaviors of other members, independently of their personal attributes (Simon 1997). With well-established routines (Nelson and Winter 1982, Cohen 2006), collaborations can be achieved without extensive interaction among the individual team members. Each person is simply doing his or her part of the job, and their intellectual products are integrated through the hierarchical organizational structure.

This is indeed the impression we had when visiting some of the large multinational R&D labs: A good team member usually means someone who “meets the expectation” of other team members. Coordination is taken care of by a team leader or manager, not by the intensive but loosely structured communications among individuals. When asked who they would turn to for information, many answered “the boss” or “the company database,” even though they admit that their foreign colleagues “are the experts on this.” Lack of direct, unstructured interactions among collaborators has constrained effective knowledge flow across distance.

2.2.2 Internal Interdependence

While lack of interpersonal interaction hinders the transfer of tacit knowledge across distance, strong technological interdependence and integrative technological structures in established organizations (Henderson and Clark 1990) may further restrict the local unit’s ability to communicate with neighbors. Large multinational firms are usually advantageous at internalizing their R&D and appropriating value from new technologies (Buckley and Casson 1976). The large number of elements in an organization and the complex interactions among them make replication nearly impossible (Rivkin 2000). Cross-regional collaborations, if carried out in a highly structured manner, only strengthen the internal linkages across the local units, making the information even more difficult to decipher by outsiders (Levin 1988).

Internal independence also leads to higher specialization of the local units’ knowledge base. Assuming pre-specified functions in a collaborative relationship, local researchers are able to contribute successfully to projects without seeing the upstream and downstream interfaces. Their partial understanding of the overall technology structure and firm-specific skill sets, in turn, limit their mobility across firm boundaries. Even if they move, their ability to convey useful knowledge to nearby firms will

be significantly compromised.

Furthermore, large firms are more likely to have the resources to exercise strategic R&D management. When a firm's R&D network spans multiple locations, at each location it can develop technologies that closely relate to the firm's internal resources residing at other locations, and use internal collaborations to achieve strategic integration. Since specialized and co-specialized complementary assets are critical to the successful commercialization of an innovation (Teece 1986, Anand and Galetovic 2004), firms can minimize knowledge outflow by increasing the interdependence of local expertise. For example, in areas where intellectual property protection is weak, firms tend to intensify the monitoring of local R&D activities and make sure that only certain stages of the discovery process are carried out locally; the resulting technologies are quickly integrated into the firm's global knowledge base (Zhao 2006). If cross-regional collaborations within a firm serve the strategic purpose of building internal complementarities, benefits from such collaborations are less likely to be shared by the local community.

3. Data Description and Empirical Setup

3.1 The Pharmaceutical Industry

The pharmaceutical industry provides the right setting for this study for several reasons. First, it is one of the most knowledge intensive industries. On average, pharmaceutical firms spend about 20% of their revenue on R&D, and innovation is directly associated with firm performance. Therefore, preventing the leakage of proprietary information and benefiting from knowledge spillovers become crucial issues in this industry.

Second, the pharmaceutical industry is highly concentrated geographically, allowing us to identify R&D locations with more certainty. A century after the industry pioneers established the first industrial R&D facilities near major research universities (MacGarvie and Furman 2005), the majority of pharmaceutical R&D is still conducted in the largest technology clusters such as the New York-New Jersey-Philadelphia region, the greater San Francisco area, London, and the Rhine Valley.

Third, the active research players in the industry fall into distinctly different camps. Large

pharmaceutical firms such as Merck and Pfizer each employs thousands of researchers worldwide, while a typical biotech startup company consists of fewer than ten scientists. This allows us to disentangle the role of firm heterogeneity from other factors in knowledge spillover.

Finally, with the pharmaceutical industry, we can take advantage of the rich information available from patent data (Henderson and Cockburn 1996, Penner-Hahn and Shaver 2005), and use the physical addresses of patent inventors to track firms' R&D activities. Both the Yale Survey (Levin *et al.* 1987) and the Carnegie Mellon Survey (Cohen *et al.* 2000) found that patents play an especially important role in protecting intellectual capital in the pharmaceutical industry. In addition, using patents granted by U.S. Patent and Trademark Office (USPTO) for the study of global R&D is justified by the dominant status of U.S. firms and the sheer size of the U.S. market. According to recent *IMS Health* reports, the U.S. market accounts for half of pharmaceutical sales worldwide; it is therefore reasonable to assume that most of the important pharmaceutical innovations would be filed for U.S. patent protection.

We apply a broad definition of the pharmaceutical industry. Following Hall *et al.* (2001), the pharmaceutical patents used in this study include the following USPTO patent classes: 424, 514 (drugs), 128, 600, 601, 602, 604, 606, 607 (surgery & medical instruments), 435, 800 (biotechnology), and 351, 433, 623 (misc.– drug & medical). We use patent classes instead of SIC codes for industry classification so as not to exclude diversified firms whose primary SIC codes are non-pharmaceutical or small firms with incomplete SIC information. Dummy variables are used to control for the possible variations across the fourteen patent classes.

To emphasize firms' internal organization, we exclude patents with multiple assignees, which are more likely to represent joint ventures or strategic alliances. Patents assigned to individuals, universities, and other non-profit organizations are also excluded. The final sample contains 204,139 focal patents,¹ of which 129,071 (62.5%) have at least one American inventor. These patents were applied for between 1975 and 2001, and were granted before the end of 2004.

¹ The number of observations in some regressions may be larger than this number because nearly 20% of the patents are observed at multiple locations.

3.2 Geography of Collaboration and Knowledge Spillover

Before studying cross-regional collaborations, we first have to define the “regions.” In the benchmark analysis, a region is defined as a metropolitan statistical area (MSA) in the U.S. – following the U.S. Bureau of the Census – or a country in the rest of the world. For the pharmaceutical industry, we prefer MSAs to states because some important technology clusters span multiple states (e.g., New York-New Jersey-Connecticut) and some states contain multiple clusters (e.g., Northern and Southern California). For other countries, few have multiple pharmaceutical R&D centers in one country, and even if they do, imposing a more refined definition throughout the world may introduce more noise than useful information. The definitions of “county” or “prefecture,” for example, vary widely across countries.

This definition generates 361 unique regions, including 263 MSAs led by New York-New Jersey, San Francisco, and Boston, and 98 foreign countries led by Japan, Germany, and the United Kingdom. Among these regions, the top five percentile is associated with more than 63% of the patents in the sample. For robustness checks, we also use country, state, or economic area – defined by the Bureau of Economic Analysis – as alternative definition of regions. The advantage of using economic areas, as compared with MSAs, is that they encompass both rural and urban counties.

The emergence of new markets and the unprecedented development of information technologies over the past several decades have had profound impact on the way R&D is carried out worldwide. Figure 1 depicts the geographic distribution of the top 5% of pharmaceutical innovators from 1975 to 2001. For each firm and each year, we count the number of locations the firm has inventors in, and calculate the Herfindahl Index of geographic concentration based on inventor locations. When the index is close to 1, the firm is concentrating almost all its R&D in a central location. Not surprisingly, the large firms significantly expanded the geographic reach of their R&D activities during this period. Meanwhile, as shown in Figure 2, the average distance among patent collaborators has been unambiguously increasing.

Insert Figures 1 and 2 here

Such organizational expansion does not necessarily indicate that the importance of geographic proximity is disappearing. It may well be that, with highly localized knowledge spillover, researchers need to remain in the clustered areas to keep pace with the fast-moving technological frontier (Leamer and Storper 2001, Sonn and Storper 2004). Thus, firms that hope to access localized knowledge have to be simultaneously present at multiple locations, and rely on internal ties for technology integration.

Figures 3 and 4 provide support for this argument. The geographic distances between all the citation dyads in the pharmaceutical industry are measured and plotted along the citation years. Interestingly, within-firm citations (Figure 3) and cross-firm citations (Figure 4) exhibit starkly different trends. While the average citation distance inside firms increased sharply between 1975 and 2001 – a trend consistent with the expansion of firm organization – the average citation distance across firms actually decreased. That is, knowledge spillover across organizational boundaries may have been increasingly localized during this period.

Insert Figures 3 and 4 here

The above figures provide some background information on cross-regional collaborations. Next, we set up the empirical framework to examine how the collaborations affect local R&D in general, and how this effect varies with firm organization.

3.3 Empirical Setup

We use the patent as the unit of analysis, as it can capture interesting variations at the technology, firm, and location levels. Two alternative models are used for the empirical analysis. Model I examines the *flow* of knowledge spillover, where the focal patents are the sources of spillover. We count the patent citations from the neighboring innovations to a focal patent, and associate them with the focal patent's cross-regional collaborative behavior. Model II examines the *result* of knowledge spillover, where the focal patents are the beneficiaries. We measure the overall quality of local patents, and associate it with the cross-regional collaborations in the region.

3.3.1 Model I: Local Citations to the Focal Patent

Patent citations are believed to be highly correlated with actual and perceived knowledge spillover (Jaffe *et al.* 2000, Lahiri 2003), despite the considerable noise in the measure (Alcácer and Gittelman 2006). In Model I, the dependent variable *local_cite* is the total number of citations from local inventors to the focal patent, excluding self-citations. To capture the knowledge spillover to local small ventures, we also calculate *local_small_cite*, a subset of *local_cite* that only includes citations from firms with less than ten patents in the observation year. Note that although this is mainly a model to explain the *level* of local citations, we will also test the *proportion* of local citations among all citations received, as part of the robustness checks.

Knowledge spillover generated by a focal patent is affected by two key factors. The first is *cross_region*, a dummy variable indicating whether the focal patent is developed by a team spanning multiple geographic locations. The second is *big_pharma*, a dummy variable indicating whether the patent belongs to a firm whose pharmaceutical patent output is among the top five percentile of the whole industry during the observation year. It turns out that these firms filed nearly half of the patents in the sample. Alternative definitions of *big_pharma*, such as the top 50 pharmaceutical companies in terms of global sales, are used for robustness tests.

The dummy variable *big_pharma* is used in addition to a continuous measure of firm size for two reasons. First, from the organizational point of view, there may be non-linear, qualitative differences between the world's largest pharmaceutical "empires" with a long history of global presence and other large firms. Second, using a dummy variable can help illustrate the marginal effects more effectively. Although this is an imperfect proxy for the concept of large established organizations, long heritage and hierarchical organization characterize most of the companies on the big pharma list.

What interests us most, however, is the interaction between *cross_region* and *big_pharma*, i.e., whether the impact of cross-regional collaborations varies across different organizational contexts. Put differently, do we observe systematic differences between cross-regional collaborations organized in large established firms and those in smaller ventures?

We also control for other patent, firm, and regional characteristics. The number of researchers on the team (*inventors*), for example, may indicate the importance of the project and its budget. In addition, a patent developed by a large organization may obtain more future citations because of higher visibility, and a patent developed in a densely populated technology center should expect more citations due to localized knowledge flow. Thus, for each year, we count the numbers of pharmaceutical patents filed by the firm (*firm_size*) and pharmaceutical patents developed in the region (*region_size*), and use their natural logarithms as control variables.

An important characterization of multi-location firms is their technological specialization at each location. For instance, some firms may prefer to develop similar expertise worldwide, while others exercise well-designed division of labor among their units. To capture this, we first calculate the overall technological similarity between every pair of regions, following Jaffe (1986):

$$s_{ij} = \frac{v_i v_j'}{\sqrt{(v_i v_i')(v_j v_j')}} \in (0,1), \quad (1)$$

where v_i and v_j are two vectors representing two regions, and the k^{th} element of v_i is the number of patents developed in region i that fall into the k^{th} patent class. A nice feature of this measure is that the absolute number of patents does not matter; only the structural distribution does. $s_{ij} = 1$ when the two vectors exactly overlap and $s_{ij} = 0$ when they are orthogonal.

Next, we go through the same calculation for each firm, and take the difference between the firm-level measure $s_{ij}^{(f)}$ and the overall s_{ij} for each regional pair (i, j) . Aggregating the differences at the firm level generates *loc_similarity*, the variable that measures whether a firm's innovation is more homogeneous – or less specialized – across its multiple R&D locations than the industry average. Interestingly, big pharma companies and small ventures demonstrate striking differences in this measure: -0.021 vs. 0.070, both significantly different from zero, the industry benchmark. This suggests that big pharma companies exercise more regional specialization than their smaller counterparts.

Finally, since citations beyond the end of the sample period are unobservable, the forward citation measure inevitably encounters data truncation problems, especially for the most recent patents (Hall *et al.*,

2001). To alleviate potential biases, we apply the *year dummies* in all regressions, and conduct robustness tests using an earlier sample period. Meanwhile, because the typical number of citations a patent receives varies across technology categories, we use the *technology dummies* to represent the fourteen primary patent classes in the sample.

The regressions are based on the following equation:

$$E(\text{local_cite}) = \beta_0 + \beta_1 \cdot \text{cross_region} + \beta_2 \cdot \text{big_pharma} + \beta_3 \cdot \text{cross_region} \times \text{big_pharma} \\ + \beta_4 \cdot \text{inventors} + \beta_5 \cdot \text{firm_size} + \beta_6 \cdot \text{loc_similarity} + \beta_7 \cdot \text{region_size} + \sigma_i + \zeta_t, \quad (2)$$

where σ_i and ζ_t are vectors of technology and year dummies, respectively. We use a cluster model to allow for the possibility that the observations are independent across firms but not within firms.

3.3.2 Model II: *Quality of Local Innovations*

Model I tracks the *flow* of localized knowledge spillover. However, it does not address the actual *result* of such spillover: whether the spillover generated by cross-regional collaborations leads to high-quality innovation by local inventors. Model II directly tests the relationship between the quality of local R&D and the cross-regional ties observed in the region.

In this model, the dependent variable is *value*, which is the count of all forward citations a patent receives after its grant date, excluding self-citations. Various studies have shown that the forward citation count serves as a good indicator of a patent's economic and technological importance (e.g., Harhoff *et al.* 1999, Hall *et al.* 2001 and 2005), which is also positively correlated with other measures of patent value, such as consumer-surplus, patent renewal rate, and contribution to market capitalization (Singh 2005b). To reduce the positive skewness observed in the citation data, we also use *log_value*, the natural logarithm of $(1 + \text{value})$, as an alternative measure.

The two key independent variables characterize the regional environment: the prevalence of long-distance collaborations in the region (*connection*), and the control of these connections by big pharmas (*conn_bpharma*). The first variable is defined as the percentage of all patents in a region that result from collaborations between local inventors and those outside the region. The second variable addresses the

organizational context of the collaborations; it is defined as the percentage of cross-regional collaborations that belong to big pharma firms. Obviously, Model I pays more attention to the *cross-firm* variations while Model II focuses more on the *cross-region* variations.

Similar to Model I, the control variables include the number of researchers on the team (*inventors*), the patent output of the firm (*firm_size*), and the region (*region_size*), as well as the *year* and *technology* dummies. In addition, we control for two region-level variables. The first is the dominance of big pharma in the region (*big_ratio*). Large firms may be more resourceful in improving the local infrastructure and attracting the best talent to town. *Ceteris paribus*, their presence should enhance the overall quality of local R&D. Hence, we use *big_ratio* to measure the percentage of patents in the region that are assigned to big pharma companies. Concerned with the correlation between *big_ratio* and *conn_bpharma*, the percentage of cross-regional collaborations organized by big pharma companies, we run regressions with and without *big_ratio* to verify the robustness of the results. The second regional variable is *tech_overlap*, the degree of technological overlap between this region and all others. Following Equation (1), for each region i , $tech_overlap_i$ is the mean of all s_{ij} 's across j . Thus, a region with a small *tech_overlap* is probably specialized in some niche areas.

The main variables are summarized in Table 1. Note that for the highly skewed variables, such as *firm_size* and *region_size*, only the logarithmic values are reported. Table 2 presents the correlations among these variables.

 Insert Tables 1 and 2 here

The regressions are based on the following equation:

$$E(\text{value}) = \beta_0 + \beta_1 \cdot \text{connection} + \beta_2 \cdot \text{conn_bpharma} + \beta_3 \cdot \text{inventors} + \beta_4 \cdot \text{cross-region} + \beta_5 \cdot \text{firm_size} + \beta_6 \cdot \text{region_size} + \beta_7 \cdot \text{big_ratio} + \beta_8 \cdot \text{tech_overlap} + \sigma_i + \zeta_t, \quad (3)$$

where σ_i and ζ_t are vectors of technology and year dummies, respectively. As in Model I, a cluster model is used to allow for the possibility that observations are not independent within firms.

4. Empirical Results

4.1 Results of Model I

In the first six columns of Table 3, we examine the number of local citations received by the focal patent, *local_cite*. To address the serious skewness in the distribution, we first take the natural logarithm of *local_cite* + 1, and run OLS regressions with technology and year dummies. The results are shown in columns (1) to (5). Column (6) is parallel to column (1), only that a negative binomial model is used to account for the discrete nature of citation counts; all the results with OLS are replicated with negative binomial models with similar statistical and economic significance.

Insert Table 3 here

The baseline results in column (1) suggest that a patent resulting from a cross-regional collaboration tends to generate more citations by local inventors. According to the marginal effect calculation, such a patent in general generates 25% more local citations than a comparable patent whose inventors are all local. However, this positive effect is seriously compromised if the cross-regional collaborations belong to one of the largest pharmaceutical companies in the world. In support of our theoretical arguments, the coefficient on the interaction term *cross_region* × *big_pharma* indicates that cross-regional collaborations in big pharmas contribute less than half to local innovation as those formed by other organizations.

In column (2), we use the interaction term between *cross_region* and *firm_size*, the continuous measure of firm size instead of the categorical variable *big_pharma*. The same pattern holds: while the coefficient on *cross_region* remains positive and significant, the coefficient on the interaction term is negative and significant. An alternative interpretation is that locating right next to a big pharma does not necessarily help. Even though patents developed by large firms, on average, generate more local knowledge spillover, this is not the case if these large firms have extensive internal linkages across geographic locations (i.e., if most of their patents are the result of cross-regional collaborations).

In column (3), we restrict the sample to the top five percentile regions in terms of pharmaceutical patent output in the observation year. Most of the theoretical discussions on localized knowledge spillover apply to densely-populated technology clusters where researchers frequently interact with one another. Yet, most of the regions in the sample generate only a handful of patents every year, locations that do not have much to do with “technology clusters.” Under the restriction, the number of distinct regions in the sample drops from 361 to 17 (seven foreign countries and ten U.S. MSAs), although they represent nearly 75% of the patent output. The results become even more significant with the restricted sample. Similar results are obtained when we restrict the sample to regions with annual pharmaceutical patent output of 100 or higher.

The factor of regional specialization enters the regression in column (4). Not surprisingly, firms that exercise more specialization than average, i.e. with a lower *loc_similarity* score, generate less knowledge spillover. Since big pharmas prove to exercise more specialization, the coefficient on the cross term *cross_region* \times *big_pharma* becomes slightly smaller in magnitude, though still negative and significant. The same pattern remains even after we include regional fixed effects in column (5).

The results obtained with the negative binomial model, as shown in column (6), are very consistent with those in the first three columns, both in the signs and magnitudes of the coefficients. The control variables also show stable results across specifications. The number of inventors on the patent, the firm size, and the level of R&D activities in the region are all positively associated with the local citations received by the focal patents.

The dependent variable for column (7) is *local_small_cite*, which counts the number of citations that the focal patent receives from local small ventures – those with less than five patents during the observation year. The only difference from the previous columns is that the coefficient on *firm_size* changes from significantly positive to insignificantly negative, suggesting that firms may be more likely to cite technologies generated from organizations of similar sizes.

Because cross-regional collaborations involve more than one location, the resulting patents would also call multiple regions “local.” Although for any particular community, what matters is the knowledge

spillover at one specific location, it is still interesting to see whether the aggregated numbers will present a different picture. In column (8), we sort out all the regions that each patent has inventors in, and sum up the citations from all these locations to measure the localized spillover. As expected, the coefficient on *cross_region* gets much higher after the aggregation, but the coefficient on the interaction term remains negative and significant, indicating the internalization effect within big pharma companies.

4.2 Results of Model II

In Model II, the overall quality of local innovation is associated with the cross-regional connections in the local community. Similar to Model I, we apply two parallel regression methods: OLS regressions on the logged dependent variable, and negative binomial models on the direct citation counts.

Insert Table 4 here

Due to the relatively high correlation between *big_ratio*, the percentage of local patents generated by big pharmas, and *conn_bpharma*, the percentage of cross-regional ties attributable to big pharmas, we leave out *big_ratio* in column (1) before putting it back into the regression in column (2). The technological overlap variable *tech_overlap* is added in column (3), and both *big_ratio* and *tech_overlap* are included in column (4). Moreover, different firms are affected by the local innovation environments to various degrees. For example, without the functional support of an established organization, small ventures are most likely affected by the activities of neighboring entities. Hence, we run the regressions on a subset of patents that are developed by firms with fewer than five patents in the observation year, and report the results in column (5). Columns (6) and (7) are simply replications of columns (1) and (4), respectively, with negative binomial regressions.

Consistently, extensive cross-regional ties contribute positively to the quality of local innovation, with the strongest effect occurring to the patents of small ventures. For an average local patent, increasing *connection* by one standard deviation will increase the expected forward citation counts by around 50%. Even after controlling for a series of regional characteristics, well-connected locations tend to produce

patents with a larger impact.

However, if the cross-regional ties are mostly formed by large pharma, the benefits may be significantly reduced, if not completely eliminated. In fact, for a region with the average *connection* level at 35% and *conn_bpharma* at 30%, having additional cross-regional collaborations formed by big pharma may only make things worse. This observation is consistent with our discussions on the role of firm organization: cross-regional ties within a large, established firm may also serve the purpose of building a closely-knit internal R&D network, making knowledge less decipherable by the neighboring R&D community.

The coefficients on the control variables are consistent with theoretical conjectures. At the patent level, the positive coefficients on *inventors* indicate that having more inventors on the team is associated with a higher value of the innovation. It also helps to have inventors from different geographic areas, as evidenced by the strong positive coefficients on *cross-region*. At the firm level, firm size seems to have a negative effect on patent value except among the very small firms. This may be due to large firms' higher propensity of patenting as suggested by Kortum and Lerner (1998) and Hall and Ziedonis (2001).

At the location level, patents developed in large technology clusters receive more citations. This is in line with the argument of localized knowledge spillover: because learning is more likely to happen locally, and because there are more potential learners in large technology clusters, patents generated in these areas tend to receive more citations in the future. The strong presence of big pharma in a region, i.e., a large *big_ratio*, is positively associated with the value of local innovations, indicating the spillover effect from the strongest players in the industry. Acs and Audretsch (1988) reach similar conclusions in their multi-industry studies. Finally, the coefficient on *tech_overlap* is positive and significant, suggesting that highly specialized regions may be less likely to produce high-impact innovations.

5. Robustness Tests and Discussions

5.1 Robustness Tests for Model I

The robustness tests on local knowledge spillover are illustrated in Table 5.

Insert Table 5 here

First, MSAs are only approximate measures of R&D locations. In the first four columns, we use two alternative definitions of “region” in the U.S.: states and economic areas. Country boundaries are still used for the rest of the world. These two alternative definitions, respectively, generate 149 and 268 unique geographic regions for the sample. The regression results, with both the 0-1 *big_pharma* variable and the continuous *firm_size* variable, remain strong and significant.

Column (5) addresses the concern over the excessive number of zero local citations. In fact, over half of the patents in the sample had never received any citations from the local community by the end of the sample period, which may be due to the short observation window or the patents’ low intrinsic value rather than firms’ strategic knowledge internalization. Hence, we apply a zero-inflated negative binomial model to allow for alternative mechanisms that may underlie the observations of zeros. The total number of forward citations is used as the exposure variable, so essentially we are testing the proportion of forward citations that happened locally. The result does confirm the possibility that the observation window is a significant predictor of the excessive number of zeroes in the dependent variable, but we find no significant changes to the coefficients of the key variables.

One caveat is that firm organization is not exogenous; instead, firms strategically organize their R&D activities in response to external environments. For example, locations with an inadequate supply of human capital and a weak technological base will find it more difficult to attract industry leaders to set up R&D centers there. Once they do, the firms’ local subsidiaries are more likely to maintain close connections with headquarters for technical support. Thus, both the cross-regional collaborations and the low local citation counts may simply reflect the weak R&D capabilities in the region. In column (6), we allow for endogeneity of the focal variable *cross-region*, as well as its cross term with *big_pharma*, by applying a three-stage least squares regression, where the decision to engage in a cross-regional collaboration is dependent on the location’s characteristics and the amount of R&D the firm has locally.

The results support the argument that non-cluster areas are more likely to see cross-regional collaborations, but the results with the focal variables get even stronger.

Next, we test the appropriate definition of big pharma. Since the analytical focus here is on the role of firm organization, we want to pay particular attention to the way firms are characterized. In the baseline analysis, firm size is measured by the total number of patents filed in the observation year. Although the overall size is important, it may not reflect the R&D activities a firm carries out at a specific location. In column (7), we redefine big pharma as those belonging to the top five percentile in terms of global innovation while having at least 20% of their patents developed locally. The results remain strong.

Finally, the number of forward citations received by a focal patent is highly dependent on the time horizon in which the citations are observed. Hall *et al.* (2001) show that it took ten years for the 1975 patents to receive 50% of their forward citations. Even with the year fixed effects, the dependent variable can still be too noisy a proxy for the most recent patents. In column (8), we conduct the analysis on patents granted before 1995, which leaves at least a ten year observation window. All the key results remain with this much smaller sample.

5.2 Robustness Tests for Model II

The robustness tests on the quality of local patents are illustrated in Table 6. OLS regressions on the logged dependent variable are used except in column (5).

Insert Table 6 here

As in Table 5, the first four columns in Table 6 test the alternative definitions of regions using states and economic areas, respectively. Regressions both with and without the variable *big_ratio* are presented. The results are highly consistent with the findings with MSAs. Column (5) addresses the excessive observations of zeros in the dependent variable. Nearly a third of the patents in the sample never received a citation other than from the innovating firms themselves, and again, the short observation window may be a factor. After allowing for this alternative explanation of excessive zeros,

we find the same strong results for the focal variables as in Table 4.

The endogeneity issue is again raised in column (6), where two key variables are treated as endogenous. First, as in Model I, the decision to form cross-regional collaborations may be dependent on the availability of local resources. Second, the percentage of cross-regional ties attributable to big pharmas may be determined by the sheer dominance of big pharmas in local R&D. Both these conjectures are supported by the simultaneous equations, but the coefficients in the main equation are still significant with the expected signs.

Lastly, to address the truncation problem, we break the sample into two periods: the first from 1975 to 1994 and the second from 1995 to 2001. The main results hold in both periods, confirming the robustness of the findings. The negative moderating effect of big pharma seems to be more significant in the second period, implying that the fast development of information technologies in the past decade may have facilitated the global firms' internalization efforts more than knowledge spillover across firms. Of course, we should exercise caution in interpreting this result, given the potential truncation problem for the second sample period.

5.3 Discussions on the Empirical Results

Admittedly, there remain considerable limitations to the empirical analysis. First, knowledge spillover is not restricted to science and technology, not to mention patentable technologies. Large firms setting up local shops may help spread information on markets, regulations, and managerial practices, which directly or indirectly affects the neighboring firms' innovation activities. These effects cannot be fully captured in this study. Moreover, our emphasis on firm organization leads to the simplification of other important dimensions, such as the strength of the collaborative ties (Hansen 1999) and the nature of the knowledge being transferred (Zander and Kogut 1995, Hansen *et al.* 2005). More information is needed for a comprehensive understanding of local interactions.

In addition, to truly capture the effect of cross-regional collaborations on knowledge flow, we need to take inventor mobility (Almeida and Kogut 1999) into consideration, both within and across firm

boundaries. For instance, due to internal mobility, R&D carried out at one location may be recorded as cross-regional collaboration when the patent is filed, and vice versa. Moreover, an employee may leave a company to start a new business (Agarwal *et al.* 2004) somewhere else. In such circumstances, patents resulting from a previous collaboration may appear as cross-regional collaborations, although they hardly reflect the incumbent firm's strategic internal organization.

The most serious limitation is that the empirical analysis does not indicate any causal relationships among the key variables. In that regard, our first-hand observations during interviews alleviate this concern to certain extent, by showing how organizational structures affect within-firm knowledge flow and cross-firm knowledge spillover beyond what can be explained by individual ties.

6. CONCLUSION

There has been a large literature on the role of interpersonal networks on knowledge transfers. It is far less understood how this role is actively shaped by the organizational context around them. By taking a closer look at a particular type of interpersonal ties – cross-regional collaborations among pharmaceutical researchers – we argue that firm organization has a significant impact on the relationship between interpersonal networks and knowledge flow. While collaborations with the outside world are generally beneficial to local R&D, the benefit can be significantly reduced if these connections are formed within large, established organizations.

Going back to the example discussed earlier, the findings in this study suggest that the Shanghaiese do have reason to celebrate the local entry of Roche's new R&D center. Industry leaders in a region usually generate more knowledge spillover and contribute to the value of local R&D. However, knowledge spillover from Roche could be very limited if the strong linkages among its multiple R&D centers also promote knowledge internalization, hence raising the learning barrier faced by the local firms. In particular, if most of a region's external interactions are realized through the internal networks of large multinational firms, other firms may benefit very little from these cross-regional ties. This study also contributes to the organization literature by suggesting that organizational structures not only affect

knowledge management directly (Argyres and Silverman 2004), but also do so indirectly by influencing the functioning of interpersonal ties. Furthermore, the implications of such interactions extend beyond organizational boundaries.

Finally, a deeper understanding of this phenomenon will have important implications to policy makers who are eager to attract investments and nurture local technology clusters. With firms' geographically dispersed R&D activities, the same scale of local R&D may generate very different knowledge spillover to the nearby firms, depending on how the knowledge is organized internally. For the local community, being part of a multinational firm's "global network" is not always a blessing.

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Figure 1. Firms Spread Out Geographically

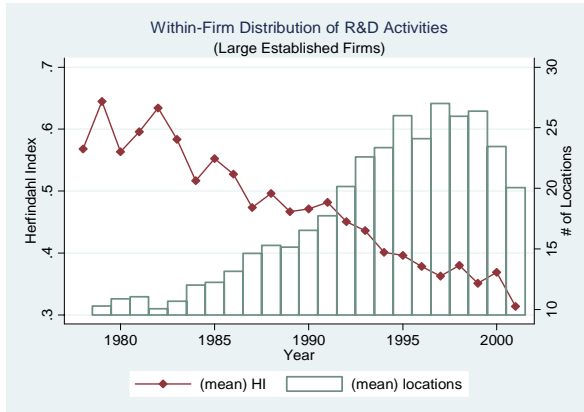
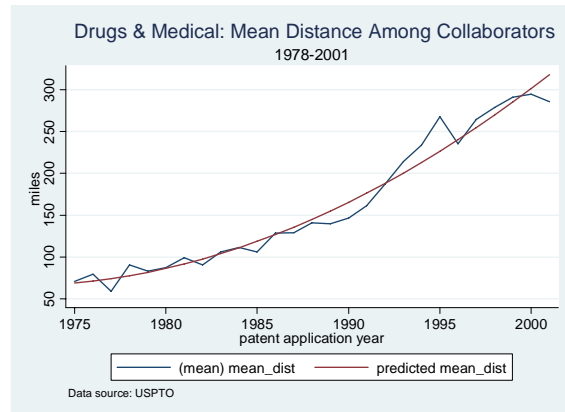


Figure 2. Cross-Regional Collaborations



- Here the criteria for large established firms are (1) top% percentile in terms of patent output, and (2) continuously in business for at least 25 years.
- Locations are defined as metropolitan areas in the U.S. and countries outside of the U.S. The same pattern remains with other definitions of location.

Figure 3. Knowledge Flow within Firms

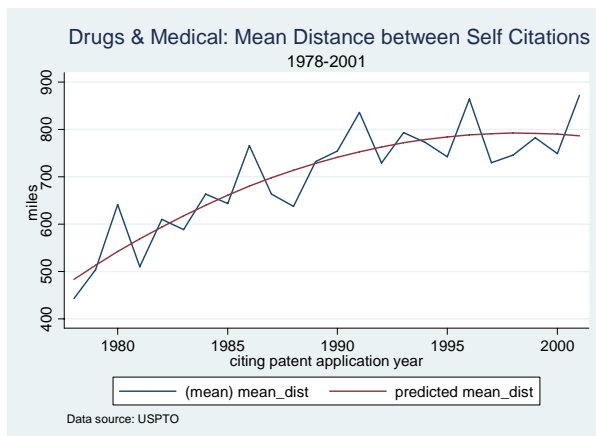
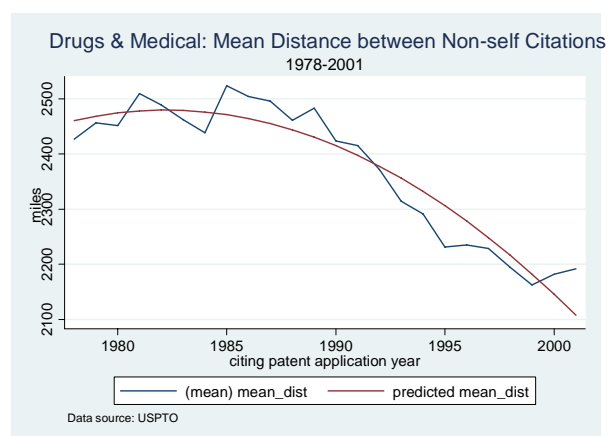


Figure 4. Knowledge Spillover across Firms



- Citation distance is defined as the mean of the pairwise distances between all inventors on the citing patent and all inventors on the cited patent.

Table 1. Summary of Variables

	Variable	Explanation	Mean	Std. Dev.	Min.	Max.
Patent level	<i>value</i>	Number of citations a patent receives, excluding self citations	6.27	14.84	0	1,075
	<i>local_cite</i>	Number of citations a patent receives from the same region, excluding self citations	1.47	5.11	0	305
	<i>local_small_cite</i>	Number of citations from local small companies, excluding self citations	0.46	1.79	0	109
	<i>inventors</i>	Number of inventors on the patent	2.55	1.73	1	32
	<i>cross_region</i>	1 if the patent is developed through cross-regional collaboration, 0 otherwise	0.17	0.38	0	1
Firm level	<i>firm_size</i>	Natural logarithm of 1 + the total number of patents filed by the firm	0.80	0.30	0.69	4.67
	<i>loc_similarity</i>	Similarity of technology classes across the firm's multiple locations	0.03	0.22	-0.93	0.99
Regional level	<i>region_size</i>	Natural logarithm of 1 + the total number of patents developed in the region	1.41	1.06	0.69	6.33
	<i>connection</i>	Percentage of all patents with inventors from multiple locations	0.35	0.42	0	1
	<i>conn_bpharma</i>	Percentage of cross-regional collaborations that are in big pharmas	0.29	0.41	0	1
	<i>big_ratio</i>	Percentage of patents granted to large firms	0.16	0.32	0	1
	<i>tech_overlap</i>	The degree of technological overlap with other regions	0.54	0.13	0	0.65
	<i>tech fixed effect</i>	Dummy variables for the 14 primary patent classes				
	<i>year fixed effect</i>	Dummy variables for the 30 grant years				

Table 2. Correlation Matrix

		1	2	3	4	5	6	7	8	9	10	11	12
1	<i>value</i>	1.00											
2	<i>local_cite</i>	0.58	1.00										
3	<i>local_small_cite</i>	0.55	0.80	1.00									
4	<i>inventors</i>	-0.04	0.02	0.03	1.00								
5	<i>cross_region</i>	-0.01	0.02	0.06	0.35	1.00							
6	<i>firm_size</i>	0.00	-0.01	-0.06	0.08	-0.12	1.00						
7	<i>loc_similarity</i>	0.05	0.03	0.01	-0.02	0.10	-0.20	1.00					
8	<i>region_size</i>	-0.10	0.00	0.02	0.08	-0.13	0.18	-0.19	1.00				
9	<i>connection</i>	-0.07	-0.05	0.00	0.05	0.34	-0.03	0.08	-0.31	1.00			
10	<i>conn_bpharma</i>	-0.08	0.00	-0.03	0.08	-0.05	0.31	-0.08	0.26	-0.05	1.00		
11	<i>big_ratio</i>	-0.06	0.02	-0.01	0.02	-0.08	0.37	-0.04	0.28	-0.03	0.78	1.00	
12	<i>tech_overlap</i>	-0.08	-0.01	0.00	0.07	-0.05	0.02	-0.12	0.16	-0.07	0.06	0.07	1.00

Table 3. Regressions on Local Knowledge Spillover

Dependent Variable: *local_cite* and *local_small_cite*

	Citations from all local inventors						Citations by local small firms (7)	Citations from multi-regions (8)
	OLS on log (1+ DV)					Negative Binomial (6)		
	(1)	(2)	cluster only (3)	(4)	location FE (5)			
<i>cross_region</i>	0.155 ** (0.011)	0.201 ** (0.015)	0.156 ** (0.013)	0.147 ** (0.011)	0.113 ** (0.005)	0.470 ** (0.044)	0.109 ** (0.008)	0.389 ** (0.014)
<i>big_pharma</i>	- 0.002 (0.020)		0.006 (0.025)	- 0.007 (0.020)	- 0.004 (0.006)	- 0.045 (0.071)	- 0.016 (0.013)	- 0.006 (0.022)
<i>cross_region</i> × <i>big_pharma</i>	- 0.080 ** (0.017)		- 0.098 ** (0.021)	- 0.073 ** (0.017)	- 0.057 ** (0.006)	- 0.243 ** (0.063)	- 0.058 ** (0.011)	- 0.085 ** (0.022)
<i>inventors</i>	0.024 ** (0.003)	0.024 ** (0.003)	0.023 ** (0.001)	0.024 ** (0.003)	0.028 ** (0.001)	0.065 ** (0.010)	0.011 ** (0.002)	0.037 ** (0.004)
<i>firm_size</i>	0.040 ** (0.008)	0.042 ** (0.007)	0.036 ** (0.010)	0.042 ** (0.008)	0.028 ** (0.002)	0.139 ** (0.026)	- 0.005 (0.005)	0.042 ** (0.009)
<i>cross_region</i> × <i>firm_size</i>		- 0.034 ** (0.006)						
<i>loc_similarity</i>				0.109 ** (0.040)	0.036 ** (0.002)			
<i>region_size</i>	0.042 ** (0.004)	0.042 ** (0.004)	0.023 (0.016)	0.043 ** (0.004)	- 0.059 ** (0.005)	0.133 ** (0.013)	0.028 ** (0.002)	0.044 ** (0.004)
<i>constant</i>	0.147 (0.092)	0.141 (0.093)	0.226 † (0.132)	0.132 (0.094)	0.668 ** (0.136)	- 1.059 ** (0.373)	0.050 (0.035)	- 0.141 (0.094)
<i>technology dummies</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>year dummies</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	247,127	247,127	157,032	247,127	238,110	247,127	247,127	247,127
<i>F</i> or χ^2	59.89	56.12	47.81	58.92	746.17	4,174.60	37.20	66.28
Prob > <i>F</i> or χ^2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Numbers in parentheses () are robust standard errors allowing for within-firm correlation except (5).

† $p < .10$

* $p < .05$

** $p < .01$

Table 4. Regressions on the Value of Local Patents

Dependent Variable: *value*

	OLS on log (1+ DV)					Negative Binomial	
	(1)	(2)	(3)	(4)	small firm patents (5)	(6)	(7)
<i>connection</i>	0.506 ** (0.042)	0.476 ** (0.043)	0.535 ** (0.046)	0.504 ** (0.048)	0.585 ** (0.037)	0.885 ** (0.083)	0.875 ** (0.088)
<i>conn_bpharma</i>	- 0.288 ** (0.039)	- 0.463 ** (0.043)	- 0.291 ** (0.040)	- 0.460 ** (0.043)	- 0.456 ** (0.036)	- 0.361 ** (0.052)	- 0.639 ** (0.062)
<i>inventors</i>	0.007 * (0.003)	0.008 * (0.003)	0.007 * (0.003)	0.007 * (0.003)	- 0.006 † (0.003)	0.024 ** (0.006)	0.025 ** (0.006)
<i>cross_region</i>	0.081 ** (0.011)	0.082 ** (0.011)	0.083 ** (0.011)	0.084 ** (0.011)	0.108 ** (0.012)	0.133 ** (0.023)	0.139 ** (0.023)
<i>firm_size</i>	- 0.026 ** (0.007)	- 0.030 ** (0.007)	- 0.026 ** (0.007)	- 0.030 ** (0.007)	0.064 ** (0.014)	- 0.033 ** (0.013)	- 0.041 ** (0.013)
<i>region_size</i>	0.018 ** (0.005)	0.015 * (0.006)	0.019 ** (0.004)	0.015 ** (0.006)	0.022 ** (0.004)	0.042 ** (0.008)	0.034 ** (0.009)
<i>big_ratio</i>		0.239 ** (0.057)		0.230 ** (0.058)	0.317 ** (0.043)		0.395 ** (0.083)
<i>tech_overlap</i>			0.140 ** (0.044)	0.129 ** (0.044)	0.176 ** (0.032)		0.242 ** (0.075)
<i>constant</i>	1.675 ** (0.140)	1.680 ** (0.143)	1.606 ** (0.144)	1.616 ** (0.146)	1.182 ** (0.291)	1.730 ** (0.211)	1.637 ** (0.218)
<i>technology dummies</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>year dummies</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	244,919	244,919	244,919	244,919	91,697	244,919	244,919
<i>F</i> or χ^2	315.26	313.25	308.61	306.97	697.71	16,551.32	16,942.25
Prob > <i>F</i> or χ^2	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Numbers in parentheses () are robust standard errors allowing for within-firm correlation.

† $p < .10$

* $p < .05$

** $p < .01$

Table 5. Robustness Tests on Local Knowledge Spillover

Dependent Variable: *local_cite*

	Alternative definition of regions				ZINB (5)	Endogenous variable (6)	Redefine big pharma (7)	Granted < 1995 (8)
	State (1)	State (2)	EA (3)	EA (4)				
<i>cross_region</i>	0.183 ** (0.011)	0.531 ** (0.040)	0.175 ** (0.011)	0.315 ** (0.028)	0.221 ** (0.026)	1.988 ** (0.102)	0.153 ** (0.010)	0.242 ** (0.018)
<i>big_pharma</i>	0.002 (0.021)		- 0.043 (0.021)		0.004 (0.054)	0.512 ** (0.034)	0.085 ** (0.017)	0.003 (0.034)
<i>cross_region</i> × <i>big_pharma</i>	- 0.096 ** (0.017)		- 0.089 ** (0.017)		- 0.210 ** (0.041)	- 2.283 ** (0.106)	- 0.087 ** (0.019)	- 0.085 * (0.034)
<i>inventors</i>	0.021 ** (0.003)	0.020 ** (0.003)	0.021 ** (0.003)	0.020 ** (0.003)	0.058 ** (0.006)	- 0.014 ** (0.005)	0.024 ** 0.002	0.022 ** (0.004)
<i>firm_size</i>	0.030 ** (0.008)	0.020 ** (0.007)	0.038 ** (0.008)	0.027 ** (0.006)	0.187 ** (0.018)	- 0.065 ** (0.002)	0.014 ** (0.005)	0.064 ** (0.018)
<i>firm_size</i> × <i>big_pharma</i>		- 0.065 ** (0.007)		- 0.032 ** (0.005)				
<i>region_size</i>	0.085 ** (0.005)	0.108 ** (0.006)	0.052 ** (0.004)	0.064 ** (0.005)	0.132 ** (0.011)	0.081 ** (0.003)	0.041 ** (0.004)	0.060 ** (0.007)
<i>constant</i>	0.017 (0.095)	- 0.078 (0.098)	0.141 ** (0.097)	0.102 (0.099)	- 2.417 ** (0.619)	- 0.327 * (0.135)	0.178 † (0.095)	- 0.066 (0.105)
<i>technology dummies</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>year dummies</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Exposure					<i>total_citation</i>			
Inflate								
<i>year</i>					- 0.171 ** (0.019)			
<i>total citation</i>					0.002 * (0.001)			
Endogenous <i>cross_region</i> =								
<i>f(cluster,</i>						- 0.098 ** (0.002)		
<i>firm local patents)</i>						- 0.002 ** (0.001)		
Observations	245,058	245,058	243,167	243,167	159,951	247,127	247,127	91,003
<i>F</i> or χ^2	66.43	60.54	64.19	60.01	2,041.07	37,761.81	64.57	20.00
Prob > <i>F</i> or χ^2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Numbers in parentheses () are robust standard errors allowing for within-firm correlation except (6).

† $p < .10$

* $p < .05$

** $p < .01$

Table 6. Robustness Tests on the Value of Local Patents

Dependent Variable: *value*

	Alternative definition of regions				ZINB (5)	Endogenous variable (6)	Granted < 1995 (7)	Granted >= 1995 (8)
	State (1)	State (2)	EA (3)	EA (4)				
<i>connection</i>	0.557 ** (0.048)	0.565 ** (0.051)	0.601 ** (0.049)	0.574 ** (0.052)	0.843 ** (0.083)	0.118 ** (0.028)	0.586 ** (0.071)	0.343 ** (0.041)
<i>conn_bpharma</i>	- 0.474 ** (0.042)	- 0.412 ** (0.050)	- 0.334 ** (0.049)	- 0.432 ** (0.049)	- 0.613 ** (0.065)	- 0.101 ** (0.022)	- 0.302 ** (0.049)	- 0.469 ** (0.052)
<i>big_ratio</i>		0.005 (0.056)		0.189 ** (0.065)	0.398 ** (0.082)		0.060 (0.060)	0.534 ** (0.058)
<i>inventors</i>	0.007 ** (0.003)	0.007 * (0.003)	0.007 * (0.003)	0.007 * (0.003)	0.025 ** (0.006)	0.007 ** (0.001)	- 0.002 (0.005)	0.013 ** (0.003)
<i>cross_region</i>	0.081 ** (0.012)	0.081 ** (0.012)	0.082 ** (0.012)	0.082 ** (0.012)	0.134 ** (0.023)	0.098 ** (0.005)	0.110 ** (0.020)	0.061 ** (0.011)
<i>firm_size</i>	- 0.030 ** (0.007)	- 0.030 ** (0.007)	- 0.027 ** (0.007)	- 0.030 ** (0.007)	- 0.042 ** (0.013)	- 0.029 ** (0.002)	- 0.051 ** (0.010)	- 0.017 ** (0.006)
<i>region_size</i>	0.046 ** (0.006)	0.047 ** (0.007)	0.026 ** (0.006)	0.022 ** (0.007)	0.034 ** (0.009)		- 0.004 (0.008)	0.022 ** (0.005)
<i>constant</i>	1.622 ** (0.145)	1.547 ** (0.148)	1.649 ** (0.140)	0.628 ** (0.143)	1.699 ** (0.217)	1.749 ** (0.167)	1.890 ** (0.154)	1.858 ** (0.054)
<i>technology dummies</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>year dummies</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inflate								
<i>year</i>					1.590 ** (0.178)			
Endogenous								
<i>cross_region = f(region_size)</i>						- 0.029 ** (0.001)		
<i>conn_bpharma = f(big_ratio)</i>						0.769 ** (0.001)		
Observations	242,744	242,744	240,040	240,040	244,919	247,127	89,159	155,760
<i>F</i> or χ^2	327.28	313.79	321.45	313.30	12,079.03	181,569.99	145.19	248.96
Prob > <i>F</i> or χ^2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Numbers in parentheses () are robust standard errors allowing for within-firm correlation except (6).

† $p < .10$

* $p < .05$

** $p < .01$