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Leveraging Knowledge Across Geographic Boundaries

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This paper examines knowledge flows within and across geographic boundaries of clusters and nations in the biotechnology industry. We hypothesize that these flows are characterized by various factors relating to the knowledge itself and by firm innovativeness and the presence of prior knowledge flows at the firm level. Surprisingly, our findings suggest that geographic proximity does not matter in some instances, while in others it has a decidedly nonlinear effect opposite to that hypothesized. The pattern of findings points to the greatest contrast in the comparison of between-cluster and between-country flows and presents an opportunity to reevaluate the role of geography and knowledge flows.

Key words: knowledge flows; regional clusters; biotechnology

Introduction

Knowledge has become accepted as the critical resource of business firms in the post-industrial economy, organizational learning the key development activity, and the acquisition of knowledge from external sources crucial to continuing innovation by firms. This paper is intended to add to the discussion of the effects of geography on the transfer of knowledge. We examine how characteristics of the knowledge transaction—of the knowledge source, the knowledge itself, and the knowledge recipient—might reinforce or mitigate the effects of geographical relationships.

The effect of geography on business has long been the focus of international business, which sees home country markets as sources of unique assets and capabilities (Dunning 1988). However, recent work in business strategy has narrowed the focus of the search for location-based competitive advantage to much smaller, more homogeneous regions, whether in the home country or in foreign locations (Porter 1998). Regional clusters, defined by Porter (2000, p. 16) as "geographically proximate group[s] of interconnected companies and associated institutions in a particular field, linked by commonalities and complementarities," are important to many industries in locations around the world, both high and low technology in nature (Porter 1998, Tallman et al. 2004).

Regional clusters (or just clusters) have been assigned particular importance in encouraging the flow of knowledge between co-located firms because of the increased use of formal and informal relationships (Saxenian 1990, Zucker et al. 1998). Empirical studies find that knowledge moves more slowly across boundaries, whether national (Kogut 1991) or regional (Almeida and Kogut 1999), and knowledge spillovers tend to be localized within boundaries (Jaffe 1989). We examine a sample of U.S. and international citations of patents held by U.S.-based biotechnology firms to ascertain whether and when interfirm knowledge flows cross the boundaries of regional clusters and nations. Our research assumes that knowledge flows are slowed by geographical boundaries and addresses two related questions: (1) Does knowledge that spans boundaries exhibit particular characteristics? and (2) Do firm-level and interfirm conditions that might supplement absorptive capacity influence the movement of knowledge across geographic boundaries?

We find that boundaries and borders do impact knowledge flows in the biotechnology industry. However, our results suggest that the admittedly simplistic, although fairly well-established, idea that knowledge flows are inversely related to distance of separation—with mitigating factors—is not an accurate empirical depiction. In fact, our findings suggest that geographic proximity does not matter in some instances, while in others it has a decidedly nonlinear effect opposite to that hypothesized. We believe that our study offers a starting point for an interesting new discussion of the relationship between geography and knowledge flows.

Model Development

Localization of Knowledge and Knowledge Flows

The strategy literature has emphasized the importance of either technical or physical proximity for one firm to access efficiently the knowledge held by other firms. Firm absorptive capacity (Cohen and Levinthal 1990) or the ability of the firm to "recognize, absorb and ... apply" (p. 129) knowledge from the environment is contingent on technological closeness. Physical proximity also facilitates the absorption of knowledge. Glaeser et al. (1992) note that "intellectual breakthroughs must cross hallways and streets more easily than oceans and continents" (p. 1127). Theoretically, this notion is bolstered by the concepts of local search (Cyert and March 1963) and the localization of knowledge (Jaffe et al. 1993), which imply that firms tend to look for new knowledge within their own geographical (and technical) neighborhoods. This insight has been applied at both the cluster level, where Storper (1995) emphasizes the importance of untraded interdependencies as the defining characteristic of a regional cluster, and at the national level, where, for instance, Kogut (1991) points to the greater speed of knowledge dissemination within a country compared with that across national boundaries.

Knowledge appears to be sticky, both nationally and in regional clusters. However, while knowledge may tend to stick to its geographical origin (Markusen 1999), clearly it does get transferred, both intentionally and unintentionally, across cluster and national boundaries. Empirically, Jaffe et al. (1993) demonstrate that, for a cohort of 1980 patents, citations were more likely to come from the same metropolitan statistical area (two to six times more likely, compared with a control group), next most likely to come from the same state (twice as likely as the control group), and finally from the same country (only 1.12 times more likely in comparison with the control group). Thus, although knowledge flows across boundaries, it appears to move more slowly as distances increase.

We compare the movement of knowledge at three levels—intracluster, intercluster, and international—as measured by the likelihood of patent citations to examine factors that limit and enhance knowledge transfer both between clusters and internationally. Research suggests that an explanation of two-party knowledge transfers can be found in the characteristics of the knowledge transaction, the condition of the knowledge source, the character of the knowledge, and the preparedness of the learning organization (Hamel 1991, Gupta and Govindarajan 2000). We therefore consider the effects of these factors manifested in technological similarity and recognized value (knowledge characteristics), originating firm innovativeness (condition of source), and prior firm linkages (preparedness of the learning organization).

We posit that proximity influences the recipient firm's ability to assess the knowledge characteristics, to evaluate the condition of the source, and to develop linkages with the source. Thus, for example, a recipient firm within the same cluster as the source firm is better able to accurately assess the value of knowledge and originating firm innovativeness and is in a better position to develop linkages with the originating firm; that firm is therefore better able to use knowledge that is not technologically similar than is a recipient firm in a different cluster, and even more so than a recipient firm in a different nation. We therefore expect a linear pattern of effects of these characteristics on knowledge flows within clusters, across cluster boundaries and across national borders.

Technological Similarity. Knowledge spillovers are created within the cluster due to various mechanisms: professional associations, informal social relationships, shared lab technicians and scientists, influence by the same core university, market exchange of information (Zucker et al. 1998), attachment to the same large chemical or pharmaceutical firms, formal alliances, and assorted forms of "backdoor knowledge sharing"—as well as through formal learning and economic transactions. The exchange of ideas and learning in the cluster will lead to greater interfirm absorptive capacity in the cluster. Therefore, knowledge flows within a regional cluster should be somewhat indifferent to specific technological constraints.

A similar development of common understanding, albeit to a lesser extent, can be seen within national boundaries, as nations develop unique systems of innovation (Bartholomew 1997, Kogut 1991). Knowledge flows between clusters and countries cannot rely on the existence of innovation communities, especially informal, face-to-face ones driven by social interaction mechanisms. Thus, in general, absorptive capacity for knowledge from firms outside the cluster will be lower and outside the country, even more so than for knowledge from firms within the cluster. However, technological similarity will increase knowledge transparency and its ease of integration across cluster or national boundaries.

Hypothesis 1. *Technological similarity increases the likelihood of knowledge flows—*

1A. *between clusters within the same country, compared with flows within clusters.*

1B. *between countries, compared with flows between clusters within the same country.*

1C. *between countries, compared with flows within clusters.*

Recognized Value. When a firm seeks external knowledge, it is likely to show greater intent for accessing knowledge that has higher publicly imputed value, particularly in the case of knowledge seekers from outside clusters who have less direct, private information about the knowledge. Furthermore, the costs associated with knowledge flows across clusters and countries are expected to be higher than those within clusters because of the need to overcome the reduced absorptive capacity that results from the lack of shared knowledge and from simple physical distance. Consequently, firms should access knowledge from other clusters or other countries only if the benefits obtained from that knowledge are expected to easily outweigh the costs. Knowledge accepted as highly valuable provides a powerful incentive to firms to overcome localization effects. In addition, highly valued, widely sought knowledge is likely to be given attention in various outlets, such as the press or international seminars and conferences and will therefore be more visible to potential users at great distances. In contrast, firms that are physically and relationally close are more likely to share knowledge of lower recognized value because of the lower costs associated with such transfers and because they share "inside information" about its actual value.

Hypothesis 2. *Higher recognized value for knowledge increases the likelihood of knowledge flows—*

2A. *between clusters within the same country, compared with flows within clusters.*

2B. *between countries, compared with flows between clusters within the same country.*

2C. *between countries, compared with flows within clusters.*

Originating Firm Innovativeness. The innovative capability of the originating firm is a representation or signal of the potential usefulness of its intellectual output. This fact should increase the learning intent of knowledge-seeking firms, particularly those from beyond cluster boundaries that have less (or no) direct informal contact with the originator. Assessment of each piece of technical knowledge may not be a feasible option, because there may be considerable uncertainty regarding the value of that knowledge to the potential user. Firm innovative capability may provide an important signal regarding firm status and consequently the quality of its knowledge. Although this signal may be considered by all firms, it should be particularly relevant to firms in other clusters and nations. In contrast, firms within a cluster should have access to multiple signals (including levels of firm innovativeness) by virtue of underlying personal and social relationships between employees of the firms, which permit more qualitative assessments of the capabilities of originators within the cluster (Saxenian 1990). However, these personal relationships will be less likely overall (though they may exist in some instances) across cluster or national boundaries, leading to greater uncertainty in assessments of value of knowledge. Thus, firms outside the cluster or country are more likely to deem knowledge to be useful on the basis of the originating firm's previous innovativeness.

Hypothesis 3. *Higher originating firm innovativeness increases the likelihood of knowledge flows—*

3A. *between clusters within the same country, compared with flows within clusters.*

3B. *between countries, compared with flows between clusters within the same country.*

3C. *between countries, compared with flows within clusters.*

Prior Firm-Level Knowledge Flows. To alleviate uncertainty regarding the value and accessibility of knowledge accessed from other firms and to increase internal receptivity for this knowledge, a firm may resort to relying on firms from which it has gained knowledge in the past. Absorptive capacity of one firm for another's knowledge is enhanced by both type of knowledge involved and similarities in firm processes and capabilities (Lane and Lubatkin 1998). Knowledge previously accessed by one firm from another is likely to have been incorporated into its internal stock of knowledge, increasing the common base of knowledge between the two firms and building a greater absorptive capacity for each other's knowledge, compared with "stranger firms." At the same time, the expected cost of accessing and integrating knowledge from unfamiliar partners is likely to be higher than for familiar partners. When the firm has not had any prior knowledge flows to or from another firm that could be a potential knowledge source, search and identification costs of the knowledge sought as well as the risk and uncertainty associated with it are likely to be higher. These costs and risks are likely to increase when knowledge is sourced across cluster and national boundaries.

Hypothesis 4. *Prior knowledge flows between firms increase the likelihood of knowledge flows—*

4A. *between clusters within the same country, compared with flows within clusters.*

4B. *between countries, compared with flows between clusters within the same country.*

4C. *between countries, compared with flows within clusters.*

Data and Methods

Research Setting

We set our study in the biotechnology industry and use patent data to track knowledge flows. Evidence from the biotechnology industry points to the dominance of certain regional clusters in innovation, such as Biotech Bay (Northern California), Biotech Beach (Southern California), Genetown (Massachusetts), and various others in the United States and to the presence of national systems of innovation (Bartholomew 1997). Further, patenting is important in the biotechnology industry and the United States is a significant source of these patents (Shan and Song 1997). Patent documents provide information regarding the firm that produces the innovation (assignee), the location of innovation (inventor location), the technology class, and the timing of innovation (patent application date). It is also possible to track knowledge flows by examining patent citation data.[1]

To construct our sample, we used the BioScan directory, which provides a comprehensive listing of biotechnology firms and their operating segments and which has been used as a data source in prior studies (Zucker et al. 2002) of the biotechnology industry. We included all U.S. biotechnology firms listed in Bioscan as operating in the human diagnostics and therapeutics segment. We then identified every biotechnology patent[2] (called original patent) that this set of firms applied for in 1990, originating from a U.S. inventor location. We restricted our original patents to those filed under the U.S. Patent System and with inventor locations in the United States. Our resulting set of firms numbered 76, because some firms had no patenting activity in 1990. We then identified all U.S. patents citing each original patent, where the assignee of the citing patent was a for-profit firm (whether U.S. based or foreign), resulting in our sample of 2,528 patents. Citations to original patents were considered for a period of eight years.[3] Self-cites are not included in our sample, so all cites reflect knowledge flows across firm boundaries.[4] Our unit of analysis is the citing patent.

Variable Operationalization

Cluster Definition. Ellison and Glaeser (1997) demonstrate that agglomeration occurs at the county, state, and cluster level. However, dynamic externalities seem to flourish in urban industrial settings, where the proximity of agents eases the sharing and exchange of information, knowledge, and learning (Krmenec and Esparza 1999, Glaeser et al. 1992). In their study on the localization of knowledge spillovers, Jaffe et al. (1993) represent the urban industrial setting by a metropolitan statistical area (MSA). We adopt their approach and use a total of 37 MSAs to represent clusters.[5]

Dependent Variables. We compared the inventor locations[6] of the original and citing patents and classified the flows as within cluster, between clusters, and between countries.

Citation within cluster. A binary variable coded as one if the inventor locations for both the original patent and the citing patent were in the same MSA, indicating knowledge flow within a cluster; zero otherwise.

Citation between clusters. A binary variable coded as one if the inventor location for the original patent was in a different MSA than that of the citing patent, indicating knowledge flow between clusters.

Citation between countries. A binary variable coded as one if the inventor location (country) of the citing patent was not the United States.

Independent Variables. These variables reflect the characteristics of the knowledge transferred and of the firms involved in the knowledge transfer.

Technological similarity. This variable reflects the similarity between the technology classes of the original patent and the citing patent. When both the original patent and the citing patent belong to the same technology class, this variable is assigned a value of one; otherwise it is zero.

Recognized value of knowledge. This variable represents the public value to the industry of the original patent, captured by total number of citations it received (not including self-citations) up to the application date of the particular citing patent. Patent citation counts have commonly been used to measure the commercial technical importance of an innovation (Narin et al. 1987).

Originating firm innovativeness. Operationalized as the number of biotechnology patents filed for by the assignee of the original patent in 1990.[7] Patent data have been used to measure technological capabilities of the firm in various high-technology industries (Praest 1998, Bachmann 1998).

Prior firm knowledge flows. This variable reflects the number of prior knowledge exchanges between the firms engaged in knowledge transfer. We used the number of citations by the citing firm of the same originating firm in the two years prior to the date of the citing patent as a measure of prior flows.[8] Prior citations of the same original patent were not considered.

Control Variables. We control for the effects of other variables that may influence knowledge flows. *Technology subclass match* is a variable that takes a value of one when the first technology subclasses of the originating and citing patent are the same and is zero otherwise (Thompson and Fox-Kean 2005). *Prior cluster/country knowledge flows* is a count of the number of prior citations between the cluster (country in case of international flows) of the citing patent and the cluster of the originating patent in the two years prior to the date of the citing patent not involving the focal dyad. Finally we include *technology class* and *originating cluster dummies*.[9] Summary statistics for our variables are presented in Table 1.

Methods. We perform bivariate logistic regressions on three subsamples, each with two types of knowledge flows.[10] Subsample 1 (Model 2A) compares citations between clusters with citations within clusters (Hypotheses A: $n1 = 1{,}756$), Subsample 2 (Model 2B) compares citations between countries with citations between clusters (Hypotheses B: $n2 = 2{,}265$), and Subsample 3 (Model 2C) compares citations between countries with citations within clusters (Hypotheses C: $n3 = 1{,}035$).

Findings

We present our findings in Table 2. Technological similarity does not increase the likelihood of a patent citation between clusters as opposed to within a cluster (Hypothesis 1A), nor between countries compared with within cluster (Hypothesis 1C). Technological similarity for citations between countries is significantly higher than for those between clusters, and Hypothesis 1B is supported.

Table 1 Means, Standard Deviation, and Correlation

Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9
Dependent variables											
1. Citation across geographic boundaries	1.20	0.61	1.00								
2. Cited within cluster	0.10	0.31	−0.67	1.00							
3. Cited between clusters	0.59	0.49	−0.40	−0.41	1.00						
4. Cited between countries	0.31	0.46	0.87	−0.23	−0.80	1.00					
Independent variables											
5. Technological similarity	0.55	0.50	0.08	−0.03	−0.06	0.08	1.00				
6. Recognized value	13.06	9.66	−0.19	0.15	0.04	−0.15	−0.13	1.00			
7. Originating firm innovativeness	37.38	30.62	0.13	−0.08	−0.06	0.12	0.14	−0.18	1.00		
8. Prior firm knowledge flows	2.61	4.81	−0.15	0.09	0.06	−0.13	0.04	0.41	0.08	1.00	
9. Prior cluster/nation knowledge flows	7.88	10.79	−0.35	0.47	−0.15	−0.15	0.02	0.28	0.03	0.43	1.00
10. Technology subclass match	0.12	0.32	0.02	−0.01	−0.02	0.03	0.33	−0.05	−0.03	−0.01	−0.01

Subgroup means	Citations within clusters	Citations between clusters	Citations between countries
Technological similarity	0.50	0.53	0.61
Recognized value	17.41	13.41	10.91
Originating firm innovativeness	30.38	35.84	42.77
Prior firm knowledge flows	3.97	2.86	1.65
Prior cluster/nation knowledge flows	27.68	14.52	5.44
Technology subclass match	0.11	0.11	0.13
N	263	1,493	772

International patent citations are more likely than intercluster citations to be in the same subsector of biotechnology. Differences in national technological institutions may reduce the ability of foreign firms to associate more distantly related biotech technologies to their own needs. The recognized value of knowledge in the original patent is not significant in Model 2A, so Hypothesis 2A is not supported. The effect of this variable across countries is significant and negative in Models 2B and 2C, contrary to the predictions of both Hypotheses 2B and 2C. International citations place less emphasis on recognized value than between-cluster and within-cluster flows. Because we infer value from the number of previous citations, and because most of our citations are by other U.S. firms, our value measure is largely based on assessments by U.S. firms, within and across clusters. Different technology regimes in other countries may lead to different assessments of the actual utility of a patent for a foreign firm as compared to a U.S. firm, and thus international citations may focus on patents that are valued highly in the foreign context, but are less cited in the United States.[11]

The greater the originating firm innovativeness, the more likely knowledge flows are to be between clusters, compared with within clusters (Hypothesis 3A) and to be between countries as opposed to between clusters (Hypothesis 3B) or within clusters (Hypothesis 3C). While Hypotheses 3A and 3B receive significant support, Hypothesis 3C is only marginally significant. This suggests that limited direct knowledge of and social interaction with originating firms that are in another cluster or country places a premium on public indicators of originating firm innovativeness, supporting our hypotheses. The hypothesized role of prior firm knowledge flows is not supported. The findings in Models 2A and 2C are not significant; and in Model 2B, prior firm knowledge flows are significantly more likely for between-cluster flows than for between-country flows, contrary to the direction in Hypothesis 4B.

Discussion and Conclusions

Research on knowledge flows has suggested that knowledge spillovers tend to be geographically bounded (Jaffe 1989, Agrawal 2002, Anselin et al. 1997). However, Jaffe et al. (1993, p. 577) suggest that the fundamental question remains as to whether there is "... any advantage to nearby firms or even firms in the same country or do spillovers waft into the ether available for anyone around the globe to grab?" Romanelli and Khessina (2005) suggest that there has been limited examination of cross-regional flows of resources. Our study provides some insights into the differential process of knowledge transfer across regional and national boundaries. Our results, with the exception of originating firm innovativeness, point to the nonlinear effects of geography on knowledge flows. The linear effect of originating firm innovativeness suggests that in situations where such proximity is lacking, the apparent competence of the originating firm at innovation is an important substitute for identification and detailed assessment of knowledge. Seeking technology from a recognized source represents a low-risk approach to knowledge sourcing when direct relationships are lacking. We might say that there is

Table 2 Logistic Regression Results for Subsample Comparison

Sample	Subsample 1: Within and between clusters Model 2A			Subsample 2: Between clusters and between countries Model 2B			Subsample 3: Between countries and within cluster Model 2C		
Dependent variable	Cited between clusters, compared with base group: Cited within cluster			Cited between countries, compared with base group: Cited between clusters			Cited between countries, compared with base group: Cited within cluster		
Independent variable									
Technological similarity	−0.33	(0.21)	H1A	0.33**	(0.10)	H1B	−0.05	(0.24)	H1C
Recognized value	0.0001	(0.01)	H2A	−0.01*	(0.006)	H2B	−0.03*	(0.01)	H2C
Originating firm innovativeness	0.01**	(0.004)	H3A	0.007**	(0.002)	H3B	0.009+	(0.005)	H3C
Prior firm knowledge flows	0.04	(0.03)	H4A	−0.08***	(0.02)	H4B	0.01	(0.04)	H4C
Controls									
Prior cluster/nation knowledge flows	−0.12***	(0.009)		0.005	0.007		−0.12***	(0.01)	
Technology subclass match	0.07	(0.30)		0.007	(0.15)		0.04	(0.32)	
Wald chi-squared	596.36			163.48			524.53		
p value	0.0000			0.0000			0.0000		
N	1,756			2,265			1,035		

Notes. All models include cluster and technology class dummies. Standard errors are indicated in parentheses.
$^{+}p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

nothing like a reputation for innovativeness to attract attention to one's knowledge base, whether between clusters or between nations.

However, the other findings regarding knowledge characteristics and prior knowledge flows do not appear to operate in this manner. They appear to have the most significant effect in the comparison of international and domestic flows and a minimal or lesser effect in the comparison of flows within clusters and between clusters that are bounded nationally. We speculate that there could be two explanations for this phenomenon. The first possibility is that proximity may not be as important in a domestic context. We conjecture that it may be the national innovation systems and the resulting common technological culture that reduce the effects of knowledge characteristics on domestic knowledge flows, resulting in a lack of significant differences. Second, it is possible that the importance of technological similarity in international flows could be an outcome of the effects of (generally) greater distances, both geographical and cultural, in international flows that make it particularly difficult to assimilate and incorporate knowledge that is technologically distant (Phene et al. 2006). Between-cluster flows, in contrast to international flows, appear ideally positioned to capitalize on exploratory learning in technologically distant areas by using the similarity created by the national context to facilitate access and absorption.

Our findings also indicate that that the characteristics of a U.S. patent that make it valuable, and thus highly cited domestically, are somewhat different from those characteristics that make a patent valuable internationally, and thus cited more internationally. Bartholomew (1997) suggests that the national institutional context, represented by various factors, such as commercial orientation, funding for basic research, tradition of scientific education, and venture capital market, shape patterns of firms' behaviors of cooperation and their use of foreign technology in biotechnology. The national institutional context appears to influence value assessments. We suspect that value assessments of knowledge are not universal but vary significantly across national contexts.

The effect of geographic distance on knowledge flows does not manifest itself in a linear manner, as hypothesized in earlier research, which relies on the concept of distance decay (Adams and Jaffe 1996, Adams 2002). Our findings offer support for opinions (Feldman 2002, Bramstetter 2002) that distance measures do not completely reflect geography, in direct contrast to the knowledge flows are inversely related to distance of separation—with mitigating factors approach used to develop our hypotheses. Although geography may create boundaries, the underlying economic and institutional structure and microeconomic linkages between firms are what is important to generating innovative activity and knowledge spillovers (Glaeser et al. 1992, Feldman and Audretsch 1999). An alternative explanation for our findings may be related to the unobserved social structure or networks prevalent within a cluster or country. An analysis of the subgroup means for prior linkages between firms shows fewer prior citations as the degree of separation increases. This finding is mirrored in the means of prior cluster/nation citation. We speculate that physical proximity increases the likelihood of knowledge exchanges indirectly by enabling the development of social networks that develop technological and innovation agendas.[12]

This study does have limitations. Our focus on the biotechnology industry limits the generalizability of our findings. We make the assumption that other countries are homogenous and cannot identify or differentiate between overseas clusters in the same foreign country. We also do not control for recipient firm innovativeness. The focus on patents means that we directly examine only articulated technology. Our reliance on patent citations to track knowledge flows raises concerns regarding patent examiner-added citations (Alcacer and Gittelman 2004) and noise in citation data (Jaffe et al. 2002), suggesting caution may be necessary in the interpretation of our findings. Our research suggests that the effects on knowledge flows operate at multiple levels: the cluster, the nation, and the international context. An interesting research direction would be to pursue an exploration of these multilevel effects.

We stated in the introduction that we assumed boundaries to have some effect in slowing knowledge transmission. The national boundary appears to be a defining border, national institutional effects slow the movement of knowledge across country boundaries, and firms within the same country are at a distinct advantage in capitalizing on domestic spillovers. However, we do find that these macrolevel influences can be overcome by characteristics of the knowledge transaction that are compatible with models of interfirm learning (Hamel 1991, Gupta and Govindarajan 2000).

Endnotes

[1]A list of citations for each patent is made through a uniform and rigorous process—patent applicants are required by law to reference any and all relevant previous patents (representing the existing knowledge that the current patent builds on) in their patent applications. This list of patent citations is further verified by a representative of the U.S. Patent and Trademark Office, the patent examiner, who is an expert in the technological area and is deemed able to identify relevant prior art that the applicant misses or conceals (Jaffe et al. 1993). In some instances the patent examiner may add relevant citations that may reflect the patent examiner's knowledge rather than the citing company's knowledge of the field, creating a limitation of our study. Since January 2001, the U.S. Patent and Trademark Office has adopted a change in reporting patent data and now includes information on examiner-added citations (Alcacer and Gittelman 2004) for those patents granted after 2001. The latest application date for the cited patents in our sample is 1998 (all original patents have a 1990 application date). However, 95% of our citations have application dates between 1990 and 1997. We also checked the average lag between the grant date and application date for our sample, and it was 1 year and 11 months. Therefore, almost all the patents in our sample were granted before 2001. Thus, data on examiner added citations are not available.

[2]Biotechnology patents were identified as those patents where the first technology class was a biotechnology class. We used the Granstrand et al. (1997) study that classified patent technology classes into 34 industry fields and identified biotechnology patents as those from five technology classes (424, 435, 436, 514, and 530).

[3]Almeida and Phene (2004) report that citation trends reveal that most patents are typically cited within six years from their application date. We allowed for an additional two years, coding citations within eight years of the application date of the original patent to get a comprehensive list of citations.

[4]Self-citations were identified as those where the same firm was the assignee of the original and citing patent. Our study is therefore limited in that it identifies self-cites only in the case of majority or wholly owned subsidiaries.

[5]We first identified the inventor city and state for each of our original and citing patents from the patent document information. Each originating and citing patent was assigned an MSA/CMSA code based on the inventor, city, county, and state information from the U.S. Census Bureau (1999). As this MSA information is only available for U.S. locations; citing patents that originated outside the United States were classified as across country flows (because all originating patents were restricted to U.S. inventor locations through our sample design).

[6]Location of first inventor named on the patent was considered.

[7]To reduce reliance on a single year measure of the firm's patenting output, we also measured firm innovativeness as a five-year stock of patents that the assignee filed between 1986 and 1990. Our findings remained the same with the alternate operationalization.

[8]The prior citations, for the firm and regional knowledge flow measures, were measured as the number of previous citations from our stock of 1990 biotechnology patents. Although we would have liked our measure to encompass other flows (such as earlier originating patents, nonbiotechnology patents), we were constrained by data limitations. The use of 1990 biotechnology patent citations provides a more conservative sample.

[9]We had a total of 5 technology classes and include 4 technology dummies with 1 class as the base group and 14 MSA dummies. There were 37 originating MSAs; however, there were 19 significant MSAs, each of which contributed at least 1% of our sample's observations. Our original runs included 19 cluster dummies for these key MSAs. Patents from five MSAs demonstrated a pattern in which they were not cited within the cluster, only by firms in other clusters or countries. When these five dummies were included in our regression runs, STATA indicated that they were predicting outcomes perfectly in the subsample runs and consequently automatically dropped the observations associated with these dummies. To ensure that we included all observations and were consistent across all regressions, we eliminated these 5 MSA dummies and included the remaining 14 MSA dummies.

[10]We created an additional dependent variable c*itation across geographic boundaries*, that takes on a value of zero for citations within clusters, one for citations between clusters, and two for citations between countries. We then ran an ordered

multinomial logistic regression, with this dependent variable on our entire sample ($n = 2{,}528$). The ordered multinomial logistic regression allows us to compare knowledge flows between clusters and between countries to a single base group, flows within clusters. Thus it can identify the hypothesized linear effects. However, in a situation where the effects are not linear, for example, if only Hypothesis 2A (recognized value increased flows between clusters compared to within clusters) was supported and Hypotheses 2B and 2C were not, the multinomial regression will not find significance for the effect of firm innovativeness. Our results, not reported here due to space constraints, indicated that only originating firm innovativeness (Hypotheses 3A–3C) has a consistently positive and significant effect. The other independent variables were either nonsignificant or marginally significant ($p = 0.1$) suggesting that binomial regressions would provide better explanations.

[11]We performed a post hoc test of recognized value in response to a reviewer suggestion, separating the total prior citations into previous domestic citations (domestic value) and previous international citations (international value). The means of total recognized value, domestic value, and international value reveal interesting differences. The total recognized value is highest for within cluster flows, next highest for across clusters, and lowest for across country flows (Table 1). While domestic value mirrors this trend (respective means are 15.87, 11.59, and 5.61), international value is the opposite (respective means are 1.54, 1.81, and 5.28), indicating that domestic and foreign firms assess value differently.

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