Industrial Clustering and Innovative Output[•]

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Abstract

The paper examines the ways firms benefit from knowledge spillovers in industrial clusters, contrasting the effects to firms not located in clusters or located in clusters not focused on the firm's application. Clustered firms are eight times more innovative when located in clusters. While the literature on organization agglomeration has highlighted a potential trade-off between the benefit and cost of co-location in terms or knowledge spillovers, our findings that agglomerations are very important to new innovative driven ventures. However, our research also indicates that although on average new ventures benefit from agglomeration, more work is needed to explore the mechanisms by which some organizations benefit from co-location and knowledge spillovers while others may not (as indicated by prior work).

Keywords: Biotechnology, industrial clustering, knowledge spillovers, R&D productivity, strategic alliances

Introduction

The idea that collocation is beneficial to a firm's innovative success is central to theorizing about the benefits of industrial clusters in the new economic growth theory and the new economic geography. Underlying the clustering phenomenon are mechanisms that facilitate the interchange and flow of information between firms, while maintaining inter-firm rivalry (Porter, 1990). If the transfer of technological knowledge is greatest for firms in close geographic proximity, then location within a cluster of related firms in a limited geographic neighborhood is expected to enhance productivity.

Central to this argument is the idea that certain locations provide localized knowledge externalities or spillovers that provide positive economic value. Because new technological knowledge is elusive and uncodified, geographic concentrations of innovative activity generate more knowledge spillovers and, therefore, more innovative output (Feldman, 1994; Audretsch & Feldman, 1996). The fact that spillovers associated with R&D activity are geographically bounded helps to account for the clustering process and to explain spatial differences in rates of innovation and the distribution of economic growth. The significance of localized knowledge spillovers as innovative inputs suggests that firms' R&D activities do not proceed in isolation, but depend on access to new ideas.

Firms that depend on innovation for their success and survival thus not only face a series of strategic decisions about the organization of their own R&D resources, including what types of strategic alliances to form but also may consider how co-location among related firms affects their productivity. Earlier studies have modeled firms' entry, growth and innovative output as a function of the strength of the cluster in which they are located, examining whether strong clusters tend to attract a disproportionate number of startups, and are responsible for a disproportionate share of innovative output (e.g., Baptista & Swann, 1998, 1999; Beaudry, 2001; Beaudry & Breschi, 2003; Swann & Prevezer, 1996).

Aharonson, Baum and Feldman (2007) explore the geographic location choice of entrepreneurial organizations and provided evidence linking the potential scope of localized knowledge spillovers and the new venture entry position. While researchers are in agreement that localization can help increase potential knowledge spillovers they also agree that these spillovers run both ways. Organizations can both benefit from the potential knowledge spillovers but also incur cost when choosing to co-locate as they have the potential to loss their own knowledge (negative spillovers). Hence some researchers argue (for example Alcacer and Chung, 2007) that organizations that have a lot of knowledge and the resources to utilize this knowledge would prefer not to co-locate while organizations that are not as strong in terms of have a large knowledge pool would prefer to co-locate. Hence, questions still remain regarding the extent to which organizations benefit from these potential knowledge spillovers.

In addition, agglomeration researchers have claimed that not all agglomerations are beneficial. In some agglomerations organizations exhibit higher innovative output more than other agglomerations. Aharonson, Baum, and Plunket (2008), examined about 7000 micro agglomerations and argued that locations vary on the degree of technological focus, resource scale, as well as emphasis on R&D investment and public and private collaboration. Building on Cohen and Levinthal (1991) argument of absorptive capacity, firms that are co-located with others with similar technological focus are more likely to be able to learn and absorb the knowledge spillovers that organizations that are not in the same technological focus. However these firms are also more at risk of losing knowledge. Hence, the trade-offs of agglomeration benefits and costs of knowledge spillovers intensify with the degree of technological focus. This beckons the question whether co-location with clusters with greater similarity of technological focus between the firms is beneficial in terms of innovative output.

In this paper, we exploit a unique, longitudinal dataset on the Canadian biotechnology industry that includes comprehensive firm level information to examine how a firm's innovative output (patent application rate) is affected (negative or positive) by co-location. We further explore whether these benefits intensify or decrease when firms locate in agglomerations that have a concentration of firms in their technological focus. Biotechnology is a type of industrial activity that would most benefit from the types of knowledge spillovers and information exchanges that are facilitated by spatial clustering. Biotechnology is likely to experience localization economies because much of its knowledge base is tacit and uncodifiable, the precise conditions that favor knowledge spillovers in agglomeration economies. Moreover, biotechnology is an industry that relies heavily on patents to protect intellectual property. Although the problems with patents as an output measure are well-known (Griliches, 1979; Scherer, 1984), they are a critical measure of inventive output for firms in the biotechnology industry with its often long delays in bringing products to market. Since many firms have not yet achieved profitability the ability to patent is a measure of the firms' success (Lerner, 1994). Patent applications are preferable to the alternative of firm growth since externalities related to knowledge should manifest themselves primarily on inventive output (Baptista & Swann, 1998).

Clustering and Firms' Innovative Output

The last decade has witnessed great interest in the topic of economic growth at the macroeconomic level (Romer, 1986; 1990). A complementary literature examines the growth of cities and suggests that localization economies increase growth within cities (Glaeser et al. 1994; Audretsch & Feldman, 1999). The benefits of clustering can be further divided into demand and supply factors (Baptista & Swann, 1998). On the demand side, firms may cluster to take advantage of strong local demand, particularly from related industries. Under certain conditions, firms can gain market share if they locate closer to competitors as originally suggested in Hotelling's (1929) celebrated analysis. Such gains may be short-lived, however, as more firms collocate, congestion results and incumbents react with intensified competition.

On the supply side, the main sources of location externalities can be traced to Marshall (1920) and Arrow (1962) and were restated by Romer (1986, 1990), and are usually referred to in the literature as MAR (Marshall-Arrow-Romer) externalities (Glaeser et al., 1994). These ideas have been augmented by recent work in the new economic geography (see for reviews Baptista, 1998; Feldman, 2000) and are reflected in Krugman's (1991) widely known work on geography and trade. MAR externalities include benefits of a pooled labor supply, access to specialized inputs and information flows between people and firms. Geographical concentration of firms in the same industry creates a market for skilled workers and specialized inputs and may lower the cost of inputs specific to an industrial specialization. The most significant supply-side externality, however, is knowledge spillovers: an industrial cluster produces positive externalities related to the diffusion of knowledge between neighboring firms.

One of the most important findings in the new economic geography is that knowledge spillovers provide a mechanism for enhancing the innovative performance and growth of firms. Knowledge spillovers arise from industry specialization as knowledge created in one firm aids the advancement of other, technologically similar firms. Geographic proximity creates opportunities for face-to-face interactions and trust building essential to the effective exchange of ideas. Moreover, uncodified knowledge leads to localized interaction to the sources of novel scientific knowledge such as universities and public research laboratories (Audretsch &

Feldman, 1996; Jaffe, 1989) and promotes networking of firms engaged in related research (Powell et al., 1996). The cumulative nature of innovation manifests itself not just at firm and industry levels, but also at the geographic level, creating an advantage for firms locating in areas of concentrated innovative activity, and leading innovation to exhibit pronounced geographical clustering. These factors can generate positive feedback loops or virtuous cycles as concentration attracts additional labor and other inputs as well as greater exchange of ideas (Krugman, 1991).

Industries that are geographically clustered should thus benefit most from knowledge spillovers, and geographic proximity concentrations of similar firms should increase innovation at the firm level. We expect, therefore, that after controlling for firm specific characteristics:

> ***Hypothesis 1 (H1). Innovative output of biotechnology firms located within geographic clusters is greater than the innovative output of those located outside such clusters.***

Clustering and Technological Specialization

It is, however, not only geographic clustering per se that produces enhanced innovative output. The importance of knowledge spillovers and information sharing on innovative activity suggest that industries that are both *spatially* clustered and *technologically* specialized should produce the greatest benefit for firms. Baptista and Swann (1998, 1999), for example, found that firms located in clusters with a concentration in their own (two-digit) industry sector produced more patents than geographically isolated firms in the biotechnology and computer industries. Concentration of firms in other (two-digit) industry sectors had no impact or even reduced patenting. Wallsten (2001) provides similar results showing that positive spillovers are greater among neighboring firms operating in the same technology area (e.g., computing, electronics, materials, energy conversion, life sciences) than across technology areas.

It is difficult to draw conclusions about the spillover effects of own and other sector effects based on such high levels of aggregation, however. Knowledge spillover arguments suggest a more fine-grained specialization, and the effects of own and other sector concentrations likely depend on the technological distance and complementarity of technological specializations. As Almeida and Rosenkopf (2003) recently found, for example, patent citation patterns within the semiconductor industry are technologically (as well as geographically) localized such that firms patenting in more similar classes were more likely to cite each other's patents. Thus, even within the same industry there is evidence that specific technological specializations matter, suggesting that greater and more interpretable evidence of knowledge spillovers will be found by examining different technological or industrial specializations within one industry.

Although biotechnology is often used to describe an industry, it is more aptly a technology for manipulating microorganisms that overtime is manifested in different specialized applications in different industrial sectors (agriculture, aquaculture, food and beverage, and human therapeutics, for example).[1] And, that the cumulativeness of technological advances and the properties of the knowledge base differ across these different specializations, rendering positive spillovers stronger within than across specializations. Thus, the more closely related biotechnology firms are in terms of their specific technological specializations, the more likely their concentration is to create virtuous, self-reinforcing effects, and exhibit greater productivity effect due to spillovers.

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1 Notably, studies of the biotechnology industry frequently consider *only* firms working in human health specializations (e.g., Powell et al, 1996; Stuart et al., 1999).

Consequently, we expect that biotechnology firms located in clusters that are strong in their own specialization should benefit more from proximity than firms located in clusters that are strong in other specializations.

> ***Hypothesis 2 (H2). Innovative output of biotechnology firms located in clusters that are strong in their own technological specialization is greater than the innovative output of those located in clusters strong in other specializations.***

Data Description

We tested our hypotheses using data on the 675 biotechnology firms operating in Canada at any time between January 1991 and December 2000. The sample included 204 startups founded during the period (of which 69 had ceased operations by December 2000) and 471 incumbents founded prior to 1991 (of which 195 had ceased operations by December 2000). We compiled our data using *Canadian Biotechnology*, an annual directory of Canadian firms active in the biotechnology field published since 1991. *Canadian Biotechnology* is the most comprehensive historical listing in existence of Canadian biotechnology firms, providing information on their management, products, growth, performance, alliances and locations. We cross-checked this information with *The Canadian Biotechnology Handbook* (1993, 1995, 1996), which lists information for a more restrictive set of *core* firms entirely dedicated to biotechnology.

Data on financings of biotechnology firms by venture capital firms and through private placements were compiled separately by the National Research Council of Canada (NRC).[2] Data on patents issued to each firm between 1975 and 2002 using the Micropatent database (which begins in 1975). We used U.S. patent data because Canadian firms typically file patent applications in the U.S. first to obtain a one-year protection during which they file in Canada, Europe, Japan and elsewhere (*Canadian Biotech '89*; *Canadian Biotech '92*).

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2 We are indebted to the NRC's Denys Cooper for permitting us to use these data

Geographic Cluster Identification

Rather than using predefined geographic units to identify clusters, we identified clusters empirically based on the relative distances between individual biotechnology firms across Canada in each observation year. This permits us to examine clustering effects over more compact geographic areas than most prior studies (an exception is Wallsten, 2001), which typically examine clustering effects using political jurisdictions such as states or counties or statistical units such as MSAs (Metropolitan Statistical Area) SMSAs (Standard Metropolitan Statistical Area). Segmenting the data in this way produces arbitrary spatial boundaries that can bisect clusters, ignoring the presence of any firms that fall beyond the arbitrary geographic boundary even if they lie very near to the borderline, and so generate inaccurate measures of the true levels of local industrial concentration. The logic of clusters suggests that firms will seek to locate be nearby similar entities based on proximity rather than on jurisdictional attributes. In our conceptualization firms self-organize, choosing locations as a strategic decision.

To identify clusters, we first converted each firm's six-character postal code address into latitude and longitude measurements.[3] In urban areas, a single postal code corresponds to one of the following: one block-face (i.e., one side of a city street between consecutive intersections with other streets – approximately 15 households); a Community Mail Box; an apartment

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3 The form of the postal code is "ANA NAN", where A is an alphabetic character and N is a numeric character. The first character of a postal code represents a province or territory, or a major sector entirely within a province. If the second character is '0', the FSA is rural. The first three characters of the postal code identify the forward sortation area (FSA). Individual FSAs are associated with a postal facility from which mail delivery originates. The average number of households served by an FSA is approximately 7,000. As of May 2001, there were approximately 1,600 FSAs in Canada (1,400 urban; 200 rural). The last three characters of the postal code identify the Local Delivery Unit (LDU). Each LDU is associated with one type of mail delivery (for example, letter carrier delivery, general delivery) and it represents one or more mail delivery points. The average number of households served by an LDU is approximately 15. As of May 2001, there were more than 750,000 Local Delivery Units.

building; an office building; a large firm/organization; a federal government department, agency or branch (Statistics Canada, 2001 Census).4 A zip code, by comparison, covers a considerably larger geographic area. Stuart and Sorenson (2003), for example, report that the mean area covered by a zip code in their study of biotechnology firm foundings is 27.4 square miles (44.41 kilometers). MSAs are larger still, with the mean area of an MSA in the U.S. equal to 10,515 square miles (17,042 kilometers).

We calculated distance by representing firms in space according to their latitudes and longitudes adjusted for the earth's curvature. Over short distances, Euclid distances would accurately measure the distance between two locations; however, the curvature of the earth seriously affects these calculations over areas as large as Canada. Therefore, we calculated distances using spherical geometry (Ng, Wilkins & Perras, 1993; Stuart & Sorenson, 2003), which computes the distance between two points A and B as:

$$d(A,B) = 6370.997 \times \{arccos[sin(latitude_A) \times sin(latitude_B) + cos(latitude_A) \times cos(latitude_B) \times cos(|longitude_A - longitude_B|)]\},$$

where latitude and longitude are measured in radians. The constant, 6370.997 is the earth radius in kilometers, and converts the distance into units of one kilometer.

Based on these measures, we constructed distance matrices comparing the location of each firm to every other firm in the population in a given year. We used these matrices as input for a cluster analysis that grouped firms by minimizing within-group average distance. Despite the substantial turnover of firms, the analysis consistently yielded thirteen distinct geographic clusters in each observation year.

4 Few firms in our sample, accounting for less than 5 percent of our yearly observations, are located in rural areas.

In each year, we compared each firm's mean within-cluster distance to the overall cluster mean, and excluded from the cluster all firms whose average distance was two or more standard deviations above the cluster average. Firms within the two standard deviation cutoff for their cluster within a given year were considered members of that cluster in that year. This process eliminated 6.2 percent of the firm-year observations from a cluster. The resulting clusters were remarkably compact, with the distance between the remaining firms located within each cluster averaging 31.7 kilometers (19.7 miles), and ranging from 1.15 to 83.19 kilometers (0.71 to 51.69 miles).[5]

Strong Technological Specialization

We identified each cluster's strong industry technological specialization(s) based on the proportions of firms in the cluster working in each technological specialization. The sixteen specializations in which Canadian biotechnology firms operate are: (1) agriculture, (2) aquaculture, (3) horticulture, (4) forestry, (5) engineering, (6) environmental, (7) food, beverage and fermentation, (8) veterinary, (9) energy, (10) human diagnostics, (11) human therapeutics, (12) human vaccines (13) biomaterials, (14) cosmetics, (15) mining and (16) contract research. We defined a cluster's strong technological specialization(s) as those in which more than 25 percent of its member firms operated.[6] To distinguish firms in their cluster's strong technological

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5 We examined the robustness of our results to this cutoff by using the overall mean distance for all clusters and defining outliers as firms that are more than two standard deviations from the overall mean. This cutoff tends to leave smaller clusters intact, while removing more distant firms from larger clusters, making them more compact. The empirical results are indistinguishable to the estimates presented in Tables 3a and 3b.

6 We examined the robustness of our results to this cutoff with a 20 percent cutoff as well as with continuous percentage variables. The empirical estimates are not substantively different from the estimates presented in Tables 3a and 3b, but are less generally efficient.

specialization, we used a dummy variable coded one if the firm's specialization was strong in its cluster, and zero otherwise.

Dependent Variable and Analysis

The dependent variable in our analysis is a firm's yearly number of patent applications. Because this variable is a count measure, we used the pooled cross-section data to estimate the number of patent applications expected to occur within a given interval of time (Hausman, Hall & Griliches,1984). A Poisson process provides a natural baseline model for such processes and is appropriate for relatively rare events (Coleman, 1981). The basic Poisson model for count data is:

$$Pr(Y_t = y) = exp\ \lambda(x_t)[\lambda(x_t)y/y!]$$

where both the probability of a given number of events in a unit interval, $Pr(Y_t = y)$ and the variance of the number of events in each interval equal the rate, $\lambda\ (x_t)$. Thus, the basic Poisson model makes the strong assumption that there is no heterogeneity in the sample. However, for count data, the variance may often exceed the mean. Such overdispersion is especially likely in the case of unobserved heterogeneity. The presence of overdispersion causes the standard errors of parameters to be underestimated, resulting in overstatement of levels of statistical significance. In order to correct for overdispersion, the negative binomial regression model can be used. A common formulation, which allows the Poisson process to include heterogeneity by relaxing the assumption that the mean and variance are equal is:

$$\lambda_t = exp(\pi' x_t)\varepsilon_t$$

where the error term, λ_t, follows a gamma distribution. The presence of $\__t$ produces overdispersion. The specification of overdispersion we use takes the form:

$$Var(Y_t) = E(Y_t)[1+\alpha E(Y_t)]$$

We estimated the model using a specification that accounts for the potential non-independence of the repeated observations on each firm. A further estimation issue concerns sample selection bias due to attrition: if a firm fails, it leaves the sample without its final activities represented in the data. Therefore, we estimated models that corrected for possible sample selection bias due to attrition using Lee's (1983) generalization of Heckman's (1979) two-stage procedure.

Independent Variables

We operationalized a biotechnology firm's investment in inventive activity using three measures: 1) R&D expenditures (in 1991 Canadian dollars, logged to normalize the distribution), 2) number of R&D employees (logged to normalize the distribution), and 3) number of R&D alliances with other biotechnology firms. We operationalized three analogous cluster-level variables computed based on the aggregate R&D expenditures, employees and alliances of *other* firms working in the same technological specialization in the cluster. Aggregate R&D expenditures and employees were again logged to normalize the distributions.

All independent variables were measured annually, and lagged one year in the analysis to avoid simultaneity problems.

Control Variables

Many other factors may influence the innovative output of biotechnology firms, which if uncontrolled, may lead to spurious findings for our theoretical variables. Accordingly, we control for a variety of additional firm, cluster, and other cluster characteristics. Unless otherwise indicated, all control variables were updated annually and lagged one year in the analysis to avoid simultaneity problems.

Firm Characteristics. First, since biotechnology firms with well-developed technological capabilities are likely to be more innovative than other firms (Amburgey et al., 1996), we control for a firm's technological competence using a count of the number of patent applications made during the last 5 years. For firms already operating in 1991, we used information on patent applications during the 1986-1990 time periods when computing the counts for the years between 1991 and 1995. This 5-year count measure follows cutoffs used in prior research (Baum et al., 2000; Podolny & Stuart, 1995; Podolny et al., 1996).

A firm's access to capital may also affect its ability to patent. For independent firms, capital raised through venture capital investments and private placements are vital to supporting inventive activity. Firms that are established as subsidiaries or joint ventures may have access to financial resources of their parent firm(s), and this may affect their level of inventive activity and likelihood of patenting. Firms may also use their revenues to support their inventive activity.

Another important source of capital for biotechnology firms in Canada is R&D grants from the NRC's Industrial Research Assistance Program (IRAP), which provides funding (up to C$350,000 per year) and expert assistance for work on R&D projects emphasizing advancement of unproven technology. Therefore, we controlled for the yearly total financing and IRAP grants received by a firm, as well as its annual revenues (all in 1991 Canadian dollars, logged to normalize the distribution). We also include a dummy variable coded one for firms with access to the resources of a corporate parent firm or firms, and zero otherwise.

Patent application rates may also vary by technological specialization. In particular, commercialization is most challenging, and so patent protection most valuable, for developments in human therapeutics and vaccines where rigorous clinical trials and regulations reduce speed to market and somewhat less so for diagnostics (about half of which are *in vitro* and half *in vivo*) (Baum et al., 2000). We control for patenting differences among firms focused on human medical specializations with a dummy variable coded one for firms in human therapeutics, vaccines and diagnostics, and zero otherwise.

In addition to R&D alliances, biotechnology firms also establish downstream alliances for manufacturing and distribution with pharmaceutical firms, chemical firms, marketing firms, and upstream alliances for basic research with university labs, research institutes, government labs, and hospitals that may affect their patent application rate. Downstream alliances link biotechnology firms to sources of complementary assets including distribution channels, marketing expertise and production facilities, as well as financing (Kogut, Shan & Walker, 1992). Upstream alliances link biotechnology firms to sources of research know-how and technological expertise that can prove critical to the successful discovery and patenting of new products or processes (Argyres & Liebeskind, 1998). To control for possible effects of these alliances on inventive output, we include separate yearly counts of a firm's number of upstream alliances and downstream alliances.

Relatedly, we control, with a dummy variable, for whether or not the firm was a university spin-off. University spin-offs may possess systematically better access to cutting-edge academic resources, or may benefit from university funds dedicated to technology transfer. We also control for firm age, defined as the number of years since founding, in our models to ensure that any significant effects of the theoretical variables were not simply a spurious result of aging-related processes.

Finally, we control for a firm's relative geographic proximity to other firms located within its cluster. Specifically, we control for the difference between a firm's average distance from others within its cluster, and the average distance between any two firms in the cluster. We expect that firms with average distances greater than the cluster average will benefit less from their cluster membership.

Table 1 gives the descriptive statistics by firms' cluster location status – in a cluster strong in its technology specialization, in a cluster not strong in its specialization, and not located within a cluster. As the tables show, the clusters vary widely in their composition and characteristics, as do firms depending on their cluster location status.

Insert Table 1 about here.

Results

Table 2 gives regression estimates differentiating the patent application rates of biotechnology firms located within and outside a geographic cluster. Controlling for firm characteristics, the coefficient estimate for a dummy variable coded one for firms located within a cluster, and zero otherwise, is positive and highly significant. Supporting hypothesis 1, this indicates that firms located within a geographic cluster out-patent those not located in a cluster. The magnitude of the coefficient is sizeable, indicating that, independent of firm characteristics, the patent application rate is more than eight times higher for firms located in clusters ($e^{2.134} = 8.45$), *ceteris* paribus.

Table 3 reports estimates for models comparing the patent application rates for firms located within a geographic cluster that is either strong in their own or another technological specialization. We found no support for hypothesis 2, which predicted that firms located in a geographic cluster strong in their industry specialization would out-patent firms located in clusters that were not concentrated in their specialization. However, we did find that the firms that had a greater than average geographic distance from other firms in their cluster had lower patent application rates than firms that were more proximate. For example, the patent application rate for a firm whose average distance was 10 kilometers further than their cluster's average was 10.4 percent below that of a firm at the average.

Several of the control variable effects are also notable. A focus on human specializations, and recent patent applications increase patent application rates. Firms with more R&D employees and greater R&D expenditures also apply for patents at a higher rate. Firms with greater revenues and more downstream alliances for manufacturing and distribution apply for fewer patents, likely because they are closer to or at the commercialization stage, and so expend less focused on innovative activity.

Discussion and Conclusion

This study set out to provide empirical evidence of whether a firm's innovative output (patent application rate) is affected - positively or negatively - by co-location. We further set to explore whether these benefits intensify or decrease when a firm locates in agglomerations that have a high concentration of firms in its technological focus. Our results show that technologically oriented new ventures benefit from being clustered. Clustered firms in the Canadian biotechnology industry are over eight times more innovative than non-clustered firms. Our finding further highlights the significance role of distance.

Prior research has provided evidence that new ventures care when choosing their location about what is available to them 5oom in radios from their location (Aharonson, Baum and Feldman, 2007). Extending prior research, our findings indicate that distance matters in terms of innovativness performance. Organizations that are located further away from their peers in the clusters tend to be less innovative in terms of patent application than do firms that are more co-located.

Taken together our findings indicate that new ventures can benefit from co-location and this benefit is significantly impacted by distance. It is not enough to co-locate in the same region / city but locating too far relative to others in that region may have similar consequences as being an outsider. Future work should examine in more detail the effect of micro locations on the innovative output of technological oriented organizations.

The results of the firm's attributes further suggests that strategic plan and actions still play a significant role in the innovativeness of organizations regardless of their location. Organization's focus on R&D vs. M&D can determine its potential innovative output. As new ventures often lack resources to do both benefiting from location may also be a function of the lifecycle stage of the firm's in that cluster. Future work can examine the potential benefits of being in a cluster in your specialization as a function of the lifecycle stage of the firms in that specialization.

However, we found no evidence to support the argument that organizations are better of co-locating in a cluster that has a concentration of organizations in their technological specializations. Hence, the question of whether organizations are better off locating in agglomerations that specialize in their technology still remains. One mean by which this question can be explored is by a closer examination of the innovative collaborative vs competitive actions of neighboring organizations and how these actions impact the innovative output of the firm. Further work should also explore the different mechanisms by which organization benefit from the knowledge spillovers as well as what actions are taken by firms that benefit from agglomerations vs the actions of the firms that fail to benefit from co-location.

References

Acs, Z. J., D. B. Audretsch, and M. P. Feldman 1994. “The Recipients of R&D Spill-overs: Firm Size and Innovation.” *Review of Economics and Statistics,* 76: 336-340.

Aharonson, B.S., Baum, J.A.C., and Feldman, M.P. 2007. “Desperately Seeking Spillovers? Increasing Returns, Social Cohesion and the Location of New Entrants in Geographic and Technological Space.” Industrial and Corporate Change, Vol.16: 89-130.

Aharonson, B.S., Baum, J.A.C. and Plunket A. 2008. “Inventive and Uninventive Clusters: The Case of Canadian Biotechnology”. Research Policy Vol. 37, 1108–1131.

Alcacer, J. and Chung, 2007. “ Location Strategies and Knowledge Spillovers”. Management Science. 53: 760–776

Almeida, P., and L. Rosenkopf 2003. “Overcoming local search through alliances and mobility.” *Management Science*, 49: 751-766

Amburgey, T.L., T. Dacin and J. Singh 1996. “Learning races, patent races, and capital races: Strategic interaction and embeddedness within organizational fields.” In J.A.C. Baum and J. E. Dutton (eds.) *Advances in Strategic Management*, 13: 303-322.

Angel, D.P. 1991. “High-technology Agglomerations and the Labor Market: The Case of Silicon Valley.” *Environment and Planning,* 23:1501-16.

Argyres, N., and J. Liebeskind 1998. Privatizing the intellectual commons: Universities and the commercialization of biotechnology. *Journal of Economic Behavior and Organization*, 35: 427-454.

Arrow, K.J., 1962. The economic implications of learning by doing. *Review of Economic Studies*, 29, 155–173.

Audretsch, D., and M. Feldman 1996. Knowledge spillovers and the geography of innovation and production. *American Economic Review*, 86: 630–640.

Balconi, M., S.Breschi and F. Lissoni 2004. “Networks of Inventors and the role of academia: an exploration of Italian patent data.” *Research Policy* 33(1): 127-145.

Baptista, R. 1998. “Clusters, Innovation and Growth: A Survey of the Literature,” in G.M.P.Swann, M. Prevezer and D. Stout, eds, *The Dynamics of Industrial Clusters: International Comparisons in Computing and Biotechnology*: 13-51. Oxford: Oxford University Press,

Baptista, R. and P. Swann 1998. “Do Firms in Clusters Innovate More?” *Research Policy* 27(4):525-40.

Baptista, R. and P. Swann 1999. “The Dynamics of Firm Growth and Entry in Industrial Cluster: A Comparison of the US and UK Computer Industries.” *Journal of Evolutionary Economics*, 9: 373-399.

Baum, J.A.C., T. Calabrese and B.S. Silverman 2000. “Don’t go it alone: Alliance network composition and startups’ performance in Canadian biotechnology.” *Strategic Management Journal*, 21 (Special Issue): 267-294.

Beaudry, C. 2001. “Entry, growth and Patenting in industrial Clusters: A Study of the Aerospace Industry in the UK.” *International Journal of the Economics of Business*, 8: 405-436.

Beaudry, Catherine, and Stefano Breschi. 2003. Are Firms in Clusters Really More Innovative? *Economics of Innovation and New Technology* 12: 325-342.

Beaudry, C. and P. Swann 2001. “Growth in Industrial Clusters: A Bird’s Eye View of the United Kingdom.” Stanford Institute for Economic Policy Research Discussion Paper 00-38.

Cohen, W.M. and D.A. Levinthal 1990. “Absorptive Capacity: A new perspective on learning and innovation.” *Administrative Science Quarterly*, 35, 128-152.

Coleman, J.S. 1981. *Longitudinal Data Analysis*. New York: Basic Books.

Collins, H.M. (1974). “The TEA Set: Tacit knowledge in scientific networks.” *Science Studies*, 4: 165-186.

Feldman, M. P. 2000. “Location and Innovation: The New Economic Geography of Innovation, Spillovers, and Agglomeration” in G. Clark, M. Feldman and M. Gertler, eds. *Oxford Handbook of Economic Geography,* Oxford: Oxford University Press.

Feldman, M.P. 1994. *The Geography of Innovation*. Dordrecht: Kluwer Academic Publishers.

Fontes, M. (forthcoming). “Distant Networking: The Knowledge Acquisition Strategies of "Out-cluster" Biotechnology Firms”. *European Planning Journal.*

Griliches, Z. 1979. “Issues in Assessing the Contribution of R&D to Productivity Growth.” *Bell Journal of Economics*, 10: 92-116.

Hausman, J., Hall, B.H., Griliches, Z., 1984. “Econometric models for count data with an application to the patents-R&D relationship.” *Econometrica*, 52: 909-938.

Heckman, J.J. 1979. “Sample selection bias as a specification error.” *Econometrica*, 47: 153-161.

Hotelling, H., 1929. “Stability in competition.” *Economic Journal*, 39: 41–57.

Jaffe, A. 1989. “Real effects of academic research.” *American Economic Review*, 79: 957–970.

Jaffe, A., M. Trajtenberg, and R. Henderson 1993. „Geographic localization of knowledge spillovers as evidenced by patent citations.” *Quarterly Journal of Economics*, 108: 577–598.

Kennedy, P. 1992. *A Guide to Econometric Methods (3rd edition)*. Cambridge, MA: MIT Press.

Kmenta, J. 1971. *Elements of Econometrics*. New York: Macmillan.

Kogut, B., Shan, W. J., and Walker, G. 1992. “The make-or-cooperate decision in context of an industry network.” In N. Nohria & R. Eccles (Eds.) *Networks and organizations*: 348-365. Boston: Harvard Business School Press.

Krugman, P., 1991. *Geography and Trade*. MIT Press, Cambridge.

Lee, L.F. 1983. “Generalized econometric models with selectivity.” *Econometrica*, 51: 507-512.

Lerner, J. 1995. Patenting in the Shadow of Competitors. *Journal of Law and Economics* 38: 463-495.

Marshall, A., 1920. *Principles of Economics*. Macmillan, London.

Mowery, D.C. 1983. "The relationship between intrafirm and contractual forms of industrial research in American manufacturing, 1900-1940." *Explorations in Economic History*, 20:351-374.

Nightingale, P. 1998. "A Cognitive Model of Innovation" *Research Policy*, 27: 689-709.

Ng E, Wilkins R, Perras A. 1993 "How far is it to the nearest hospital? Calculating distances using the Statistics Canada Postal Code Conversion File" Health Rep. (Statistics Canada, Catalogue 82-003) 1993; 5(2): 179-88.

Owen-Smith, J. & W. W. Powell (forthcoming) "Knowledge Networks as Channels and Conduits: The Effects of Spillovers in the Boston Biotechnology Community." *Organization Science.*

Podolny, J., T.E. Stuart and M.T. Hannan. 1996. "Networks, knowledge, and niches." *American Journal of Sociology*, 102: 659-689.

Porter, M., 1990. *The Competitive Advantage of Nations.* Macmillan, London.

Powell, W.W., K.W. Koput and L. Smith-Doerr. 1996. "Interorganizational collaboration and the locus of innovation: Networks of learning in biotechnology." *Administrative Science Quarterly*, 41: 116-145.

Romer, P. 1986. "Increasing returns and long-run growth." *Journal of Political Economy*, 94: 1002–1037.

Romer, P. 1990. "Endogenous technological change." *Journal of Political Economy*, 98: S71–S102.

Scherer, F.M., 1984. "Using linked patent and R&D data to measure inter-industry technology flows." In: Griliches, Z. (Ed.), *R&D, Patents and Productivity*. Chicago IL: University of Chicago Press.

Silverman, B.S. and J.A.C. Baum. 2002. "Alliance-Based Competitive Dynamics in the Canadian Biotechnology Industry," with Brian S. Silverman. *Academy of Management Journal*. 45: 791-806.

Sorenson, O. and T.E. Stuart. 2001. "Syndication networks and the spatial distribution of venture capital financing." *American Journal of Sociology*, 106: 1546-1588.

Stuart, T.E. and Sorenson, O. 2003. "The Geography of opportunity: spatial heterogeneity in founding rates and the performance of biotechnology firms." *Research Policy*, 32: 229-253.

Stuart, T.E., H. Hoang and R.C. Hybels. 1999. "Interorganizational endorsements and the performance of entrepreneurial ventures." *Administrative Science Quarterly*, 44: 315-349.

Stuart, T.E. and J.M. Podolny. 1996. "Local search and the evolution of technological capabilities." *Strategic Management Journal*, 17 (Special Issue): 21-38.

Swann, P. and M. Prevezer 1996. "A Comparison of the Dynamics of Industrial Clustering in Computing and Biotechnology." *Research Policy* 25: 1139-57.

Wallsten, S.J. 2001. “An empirical test of geographic knowledge spillovers using geographic information systems and firm-level data.” *Regional Science and Urban Economics*, 31:571-599.

Table 1. Descriptive Statistics by Geographic Cluster Status

	Not in Strong Specialization		in Strong Specialization		Not in Cluster	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Variable						
Firms Variables						
Age	15.62	20.02	12.96	16.16	19.92	21.75
University Spinoff	0.07	0.25	0.07	0.26	0.02	0.12
Corporate Parent	0.16	0.36	0.23	0.42	0.22	0.42
Human Specialization	0.35	0.48	0.65	0.48	0.12	0.33
Patent Application Last 5 Years	1.16	5.15	0.93	4.60	0.08	0.34
In (R&D expenditures)	12.65	3.12	12.38	3.88	12.90	2.66
In (R&D employees)	2.07	1.14	2.11	1.31	1.91	1.10
In (Revenues)	12.94	5.12	13.24	4.72	13.81	4.34
In (Financing)	1.02	3.80	0.77	3.34	0.09	1.07
In (IRAP Grants)	0.32	1.82	0.39	2.01	0.30	1.70
upstreeam alliances	1.21	1.94	1.19	1.89	0.85	2.70
downstream alliances	0.97	3.09	1.77	3.45	2.62	8.98
R&D alliances	0.32	0.85	0.47	0.88	0.08	0.27

Note: The sample included 1930 yearly observations for firms not in the strong sprcialization of their cluster, 508 yearly obsrevations for firms in the strong specialization of their cluster, and 132 yearly observations for forms not locates

Table 2. Negative Bionomial Regression Model of Patent Application Rates of Firms Located Within and Outside Geographic Clusters

Firms Variables	Coef.	S.E	
Age	0.003	0.005	
university spinoff	0.134	0.368	
corporate parent	0.989	0.292	***
Human Specialization	1.369	0.209	***
patent application last 5 years	0.094	0.029	***
In (R&D expenditures)	-0.049	0.032	+
In (R&D employees)	0.465	0.079	***
In (Revenues)	-0.045	0.018	**
In (Financing)	-0.022	0.018	
In (IRAP Grants)	-0.032	0.031	
upstreeam alliances	-0.047	0.042	
downstream alliances	-0.078	0.029	**
R&D alliances	-0.082	0.07	
Cluster Variables			
located within a geographic cluster	2.134	0.708	**
Heckman Correction	-17.171	4.152	***
Constant	-3.008	0.819	***
Coverdispersion Parameter	4.183	0.521	***
Log-Likelihood	-920.26		

Note: +p<.10, *p<.05, **<.01, ***p<.001. The sample includes 2121 yearly observations for all firms. All independent variables are lagged one year

Table 3. Negative Bionomial Regression Models of Patent Application Rates by Firms Located within a Geographic Cluster

	β	S.E	
Firms Variables			
Age	0.001	0.005	
university spinoff	0.897	0.304	**
corporate parent	0.500	0.235	*
Human Specialization	0.963	0.186	***
patent application last 5 years	0.145	0.029	***
ln (R&D expenditures)	0.052	0.030	*
ln (R&D employees)	0.491	0.079	***
ln (Revenues)	-0.038	0.017	*
ln (Financing)	-0.008	0.017	
ln (IRAP Grants)	0.031	0.030	
upstreeam alliances	-0.047	0.042	
downstream alliances	-0.049	0.028	*
R&D alliances	0.018	0.069	
Firm in Strong Specialization	-0.155	0.214	
Firm vs. Cluster Average Distance	-0.010	0.004	**
Heckman Correction	-5.502	2.015	**
Constant	-2.143	0.445	***
Overdispersion Paramete	4.297	0.521	***
Log Likelihood	-911.17		
Likelihood Ratio Test vs. Nested Model (df)			

Note: +p<.10, *p<.05, **<.01, ***p<.001. The sample includes 2013 yearly observations for firms located within a geographic