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by

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Abstract:
We examine how industrial clustering affects biotechnology firms' innovativeness, contrasting similar firms not located in clusters or located in clusters that are or are not focused on the firm's technological specialization. Using detailed firm level data, we find clustered firms are eight times more innovative than geographically remote firms, with largest effects for firms located in clusters strong in their own specialization. For firms located in a cluster strong in their specialization we also find that R&D productivity is enhanced by a firm's own R&D alliances and also by the R&D alliances of other colocated firms.

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

JEL Codes: O31, R30

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Introduction

The idea that collocation is beneficial to firms' 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 colocation 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). These studies yielded a number of important findings, most notably, that, compared to more isolated firms, firms located in clusters that were strong in their own broadly defined (2-digit) industry tended to grow faster and produce more innovations, while firms located in clusters that were strong in other (2-digit) industries did not. What these studies do not consider, however, is why this is the case: data limitations prevent estimation of firms' relative benefit from knowledge spillovers when compared to similar firms that are geographically isolated or located in non-specialized clusters. Moreover, one means firms may use to source knowledge and overcome geographic isolation is through the formation of strategic alliances yet there has been limited investigation of how this firm strategy relates to geographic location and if strategic alliances provide substitutes or complements for colocation.

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 by its own and other collocated firms' R&D inputs (R&D expenditures, R&D employees and R&D alliances). We contrast the effects of these R&D inputs for firms located in clusters that were strong in their technological specialization (e.g., agriculture, aquaculture, human therapeutics) with the effects for firms located in clusters that were not strong in their specialization. This permits us to examine the extent to which the greater innovativeness of firms located in clusters strong in their own technology specialization result, at least in part, from their earning greater returns to R&D activity as a result of enhanced knowledge spillovers.

Our study makes four additional empirical contributions made possible by our comprehensive firm-level data. First, whereas data limitations have limited prior studies' ability to control for firm heterogeneity, we are able to specify a detailed firm-level baseline model to help ensure that observed clustering benefits are not spuriously capturing uncontrolled firm characteristics. Second, our detailed firm level information enables us to model the influence of a broader range of cluster characteristics on innovative output than past research, which has focused primarily on cluster employment. Third, we are able to specify firms' technological specializations in a much more fine-grained way than most past studies, which have relied on much broader industry or sector definitions that made it difficult to draw strong conclusions about own and cross-sector spillover effects. And fourth, we identify geographic clusters empirically based on the relative geographic locations of individual firms, permitting us to examine clustering effects over compact geographic areas. After all, we expect that clusters will be defined by the self-organization of firms. Data constraints have forced most past studies to examine cluster-related effects based on predefined administrative or statistical units such as states or metropolitan areas despite evidence that spillovers and other agglomeration externalities are stronger in smaller geographic areas (Jaffe et al., 1993).

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 to 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 particular technological specializations, the more likely their concentration is to create virtuous, self-reinforcing effects, and exhibit greater productivity effect due to spillovers.

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.***

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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).

Clustering and the Returns to Firms' Own and Other Firms' R&D Activities

Hypothesis 2 begs the question: What are the precise advantages provided by geographic proximity to creative, knowledge intensive innovative activity? As Balconi et al. (2004) note, we still know little about knowledge transport mechanisms. Informal conversations and personal social networks are, however, widely believed to be vital mechanisms for transferring knowledge and ideas between firms. Networks play an important part in many economic phenomena, and one area in which networks are particularly important is the diffusion of information and knowledge. The tacitness of cutting-edge knowledge highlights that successfully applying knowledge to commercial activity entails an intensive and costly investment (Nightingale 1998). Collins (1974), for example, found that even after publication of results, no scientist was able to build a TEA laser without having first spoken directly with members of the original research team. Even patents, which contain codified knowledge, exhibit a strong geographic element to their diffusion. Jaffe et al. (1993), for example, find that patent citations are more likely to come from within the same state and SMSA, arguing that this reflects underlying patterns of research activity. Almeida and Rosenkopf (2003) recently found a similar pattern of geographically localized patent citations in the U.S. semiconductor industry.

Diffusion of knowledge and ideas tends to be local rather than global, and for early stage technological specializations when tacitness is high, face-to-face contact becomes increasingly essential to effective knowledge transfer. Concentrating people engaged in related activities in a particular location thus creates an environment that facilitates the rapid and effective diffusion of ideas. Close proximity may thus not only be helpful in capturing knowledge spillovers – but necessary.

Taken together, these ideas about transport mechanisms suggest that, whatever the mechanism, strong clusters exist because concentrating the R&D activities of firms facilitates knowledge spillovers in a given technological specialization, thereby increases the productivity of R&D activity – R&D expenditures, R&D employees and R&D alliances – for each firm in the concentration. Moreover, research shows that firms that conduct their own R&D are better able to use externally available information (e.g., Mowery, 1983); suggesting that absorptive capacity – the ability to exploit external knowledge – is created as a byproduct of a firm's R&D investment (Cohen & Levinthal, 1990). R&D experience enables a firm to recognize and exploit relevant new information and identify useful complementary expertise outside the firm. A firm's

R&D thus not only generates new knowledge but also contributes to its absorptive capacity. This suggests that the greater innovativeness of firms located in clusters that are strong in their own technological specialization results not only from their earning greater returns to their own R&D activity but also from a key source of the spillovers: the R&D activities of other firms working on the same technological specialization. Therefore, we hypothesize:

Hypothesis 3 (H3). A biotechnology firm's innovative output is enhanced more by its own R&D activities when it is located in a cluster that is strong in its own technological specialization than when it is located in a cluster strong in another specialization.

Hypothesis 4 (H4). A biotechnology firm's innovative output is enhanced more by the R&D activities of other firms in the same technological specialization when it is located in a cluster that is strong in its own specialization than when it is located in a cluster strong in another specialization.

An alternative interpretation of the forgoing argument is that, rather than enhancing the value of a firm's own R&D activities, the positive externalities afforded a firm located in a cluster strong in its own technological specialization renders the firm's own R&D activities redundant. That is, that cluster membership may substitute for a firm's own R&D activity (Acs et al. 1994). For example, while R&D alliances may represent important conduits for the exchange of ideas and knowledge, firms located in clusters that are strong in their own industrial specialization may use informal networks and interactions instead, which would decrease the need for such formal collaborative arrangements. In the same way, greater informal exchange of ideas among R&D employees across firm boundaries may substitute for the exchange of ideas among R&D employees within a firm's boundaries. If this were the case, in contrast to hypotheses 3 and 4, we would expect that firms located in clusters that are not strong in their own industrial specialization benefit more from R&D alliances and investments in R&D employees. When firms do not have access to the informal networks and interactions that characterize the strong geographic R&D concentration they may compensate with formal strategic alliances.

Moreover, at the cluster level, it is also likely that there are limits to the positive externalities by which clusters are self-reinforced, and that as a cluster grows, congestion and competition effects arise that may negate the positive agglomeration benefits. Thus, rather than greater positive externalities, more R&D activity by firms in the same industry may generate greater competition among firms in the cluster for, for example, skilled R&D employees (Baptista & Swann, 1998) or R&D alliance partners (Silverman & Baum, 2000) and so impedes, rather than enhances a firm's innovative output. Altogether, these ideas suggest the following alternative hypotheses:

Hypothesis 3alt (H3alt). A biotechnology firm's innovative output is enhanced less by its own R&D activities when it is located in a cluster that is strong in its own technological specialization than when it is located in a cluster strong in another specialization.

Hypothesis 4alt (H4alt). A biotechnology firm's innovative output is enhanced less by the R&D activities of other firms in the same technological specialization when it is located in a cluster that is strong in its own specialization than when it is located in a cluster strong in another specialization.

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

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

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*).

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 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

[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.

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

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, Euclidian 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's 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.

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] Figure 1 shows the geographic distributions of biotechnology firms in Canada for 1991 and 2000, and the geographic locations included within each of the empirically derived clusters for these years. Overall, the industry is highly clustered within a small number of compact areas.

[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 from the estimates presented in Tables 3a and 3b.

Insert Figure 1 about here.

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.

Insert Figure 2 about here.

Figure 2 plots the distribution of firms by cluster (labeled based on the province in which the majority of firms reside) among seven of the above industry technological specializations covering over 85 percent of the sample firms. The figure indicates that the majority of clusters are dominated by activity in human therapeutics and/or human diagnostics. Exceptions include the Saskatchewan and Alberta-2 with concentrations in agriculture, Quebec-2 and New Brunswick with concentrations in engineering, and Nova Scotia, Prince Edward Island and Newfoundland with concentrations in aquaculture. Based on the distribution in Figure 2, 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 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

[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.

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, ε_t, follows a gamma distribution. The presence of ε_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 period 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.

Own Cluster Same Specialization Characteristics. At the cluster level, we controlled for a set of analogous variables by aggregating the annual financing, IRAP grants, revenues of other firms located in a firm's cluster and working in the same technological specialization (all in 1991 Canadian dollars, logged to normalize the distribution), as well as yearly counts of their upstream and downstream alliances. We also controlled for inventive output at the cluster level by aggregating patent applications made during the last five years by other firms working in the same specialization in the cluster. These patents may represent a key source of knowledge spillovers; alternatively, they may serve to foreclose more technological opportunities.

In addition, we controlled for potential local competition using a count of the number of other firms located in the firm's cluster working in the same technological specialization. Finally, prior research has shown that the proximity to sources of scientific discovery can enhance firms' inventive output (e.g., Jaffe, 1989; Feldman, 1994). Therefore, we control for the number of university research labs working in the same specialization and located within the geographic bounds of a firm's cluster.

*Own Cluster Other Specialization Characteristics***.** To account for the possibility that any own cluster same specialization effects we found were not spuriously capturing broader cluster-level, but not specialization-specific effects, we recomputed each of the own cluster same specialization variables, by aggregating the same information for firms working in *other* specializations within the cluster.

Other Cluster Same Specialization Characteristics. Additionally, to ensure that any effects we found of clustering were not spuriously capturing a more diffuse (i.e., non-local) processes occurring at a national level, rather than cluster level, we recomputed each of the own cluster variables, by aggregating the same information for firms located in all other clusters.

Table 1a gives descriptive statistics by geographic cluster. Table 1b 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 Tables 1a and 1b about here.

Appendix Table A1 presents descriptive statistics and bivariate correlations for independent and control variables for the analysis of patent application rates. Our analysis may be affected by moderate multicollinearity among some of our explanatory variables, which can result in less precise parameter estimates (*i.e.*, larger standard errors) for the correlated explanatory variables but will not bias parameter estimates (Kennedy, 1992). Although moderate multicollinearity does not pose a serious estimation problem, it may result in conservative tests of significance for correlated variables, making it difficult to draw inferences about the effects of adding particular variables to our models. Therefore, we estimate and test the significance of groups of variables in comparisons of a series of hierarchically nested regression models and examine coefficients' standard errors for inflation to check that multicollinearity is not causing less precise parameter estimates (Kmenta, 1971). Although we do observe a small degree of standard error inflation in relation to the interaction effects, our ability to judge the significance of individual coefficients is not materially diminished.

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 3a 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. Model 1 provides a baseline model that includes firm characteristics, including a dummy variable coded one for firms located in a cluster strong in their industrial specialization, and zero for firms located in clusters strong in a specialization other than their own, as well as the firm's distance from other firms its cluster. Models 2, 3 and 4 build clustering effects into the baseline, adding, respectively, characteristics of the firm's own cluster in the same specialization, other specializations in the firm's own cluster, and the other clusters to ensure that effects of the own cluster characteristics are not spuriously capturing a more diffuse set of processes unrelated to technological specializations or geographic proximity.

In Table 3b, Models 5 through 8 add the strong specialization interactions to examine in more detail the effects of the concentration of R&D activity within clusters on firms' patent application rates. Models 5 and 6 introduce interactions of strong specialization with a firm's own R&D activity and other firm's R&D activity separately; Model 7 includes both. Model 8 drops the insignificant interactions with own and other firm's R&D expenditures. As likelihood ratio tests given in the table show, Model 8 provides a significant improvement over Model 4. Therefore, we interpret the interaction effects in Model 8, our best fitting model.

The significant positive coefficient in the fully specified model for the Firm in Strong Specialization dummy variable supports 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. Although not as large as the effect of being located in a cluster, firms located in clusters that were strong in their technological specialization applied for patents at more than twice the rate of firms not located in clusters strong in their specialization ($e^{0.931}$= 2.54).

Support for hypothesis 3 is mixed, but consistent across levels. The significant negative coefficient for the Strong Specialization x Firm R&D Employees interaction supports hypothesis 3alt. The significant positive coefficient for the Strong Specialization x Firm R&D Alliances interaction supports hypothesis 3, however. The coefficient for Strong Specialization x Firm R&D Expenditures is not significant. The pattern of results is identical for hypothesis 4. The significant negative coefficient for the Strong Specialization x Own Cluster Same Specialization R&D Employees interaction supports hypothesis 4alt, while the significant positive coefficient for the Strong Specialization x Own Cluster Same Specialization R&D Alliances interaction supports hypothesis 4. The Strong Specialization x Own Cluster Same Specialization R&D Expenditures interaction is not significant.

Figures 3a and 3b illustrate the implications of these interactions graphically. Figure 3a shows that as a firm's own and other same specialization firms' R&D employees increase in number, patent application rates for firms located in clusters that are strong in their own technological specialization falls from 2.0 times greater than firms located in clusters that are not strong in their own specialization when a firm has three R&D employees (i.e., natural logarithm = 1), to 1.1 times greater when the firm's number of R&D employees reaches 20 (i.e., natural logarithm = 3), and from 1.5 times greater when other same specialization firms' have 55 R&D employees (i.e., natural logarithm = 4) to 0.73 times when other firms' number of R&D employees reaches 245 (i.e., natural logarithm = 5.5).

Figure 3b shows, in contrast, that as a firm's own and others firms' R&D alliances increase in number, patent application rates for firms located in clusters that are strong in their own technological specialization increases from 2.6 times greater than firms located in clusters that are not strong in their own specialization when a firm has no R&D alliances, to 27.4 times greater when the firm's number of R&D alliances reaches five, and from 2.5 times greater when other same specialization firms' have no R&D alliances to 16.3 times greater when other firms' number of R&D alliances reaches 15.

Taken together the estimates indicate that the greater innovativeness of biotechnology firms located in clusters that were strong in their own specialization stemmed from two mechanisms. One is that they earned greater returns to their own R&D alliances and from the R&D alliances of other firms in the same specialization. Consistent with hypotheses 3 and 4, this suggests that formal mechanisms for information exchange and knowledge transfer among firms in the cluster enhanced their research productivity in the presence of greater of spillovers.[7] Notably, in the absence of main effects for Firm R&D Alliances and Own Cluster Same Specialization R&D Alliances, the significant positive interactions of these variables with Firm in Strong Specialization indicate, strikingly, that R&D alliances enhanced innovative output *only* for firms located in clusters strong in their specialization. These findings point to the significance of R&D alliances to a firm's ability to exploit external knowledge; that is to its absorptive capacity.

The other is that their access to knowledge spillovers in the informal networks and interactions that characterize strong R&D concentrations served as a partial substitute for access to information and ideas through formal employment relations. As indicated by the combined significant positive Firm R&D employees main effect and significant negative Strong Specialization x Firm R&D Employees interaction effect, firms located in clusters strong in their own specialization actually benefited *less* from their own R&D employees, consistent with hypothesis 3alt. However, consistent with hypothesis 4alt, in the absence of main effect of Own Cluster Same Specialization R&D employees, the significant negative Strong Specialization x Firm R&D Employees interaction points to the limits of agglomeration – as a cluster's strong specialization grew competition among firms for skilled R&D employees dampened the positive externalities generated by the R&D concentration.

[7] Although our data do not permit us to determine where a firm's R&D partners are located, other studies have shown the tendency for interfirm alliances to be geographically localized (e.g., Sorenson & Stuart, 2001).

Several of the control variable effects are also notable. Among firm characteristics, corporate parents, a focus on human specializations, and recent patent applications increase patent application rates. Firms with more R&D employees and greater financing 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. The negative effect for R&D expenditures is somewhat puzzling, but may also be attributable to a life-cycle effect – *ceteris paribus*, firms with greater R&D expenditures may be engaged in more basic research, and so to apply for fewer patents. In addition, when the firms' research requires clinical trials before the product can be commercialized, and since clinical trials demand much of the firm's resources, the firms are more inclined to focus their attention, at those stages, on the successive completion of the clinical trials phases rather than on new patents applications. Finally, a firm's proximity *within* a cluster matters. Firms that were 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.

Among *own* cluster *same* specializations characteristics, a firm's patent application rate was higher when more same specialization university labs were located in its cluster. IRAP grants to other firms in the same specialization also raised a firm's patent application rate, suggesting a rising tide for all firms in specializations attractive to this government funding agency. Greater financing of other firms in the same specialization, however, lowered a firm's patent application rate, suggesting intra-cluster, intra-specialization competition for financial resources. The negative effect of other same specialization firms' upstream alliances may reflect either competition for access to scarce innovative capabilities of university, research institute, and government labs, or a life cycle effect (i.e., specializations characterized by a high frequency of upstream alliances are likely focused on early-stage research). The negative effect of other same specialization firms' downstream alliances likely reflects a life cycle effect since specializations characterized by a high frequency of downstream alliances are focused on commercialization, resulting in less resources being devoted to R&D.

Among own cluster other specializations characteristics, we again find traces of competition and commensalism. There is evidence of competition in the negative coefficient for the number of other firms in other specializations in several models (see Models 6-7). The coefficient for IRAP grants to firms in other specializations is, however, positive, suggesting a 'rising tide for all' in clusters attractive to this government funding agency – regardless of specialization. The positive coefficients for other specialization revenues and downstream alliances may reflect a life cycle effect: specializations with higher revenues and more downstream alliances are likely focused on commercialization, not on R&D.

The effects of *other* cluster *same* specialization characteristics exhibit a distinct nature of inter-cluster competition, providing further evidence of the veracity of the clustering effects. In particular, while recent patent applications and R&D expenditures by same specialization firms within a firm's own cluster did not affect its patent application rate, recent patent applications and R&D expenditures by same specialization firms in other clusters lowered its rate of application. The negative effect of same specialization firms' upstream alliances in other clusters may again reflect either a specialization-specific life cycle effect, or inter-cluster competition for access to scarce innovative capabilities of university, research institute, and government labs. The positive coefficient for revenues of same specialization firms in other clusters may suggest the existence of national patent races as positive revenue in a technology spurs on additional inventive activity.

Discussion and Conclusion

This study set out to provide empirical evidence of the specific ways in which firms benefit from knowledge spillovers and externalities in industrial clusters. A rich data enabled us to specify a detailed baseline model and examine the influence of a broader range of cluster characteristics on innovative output and to examine firms' technological specializations in a very fine-grained way. The firm level controls, along with controls for industry activity in other specializations in the same cluster, and the same specialization in other clusters, help ensure that our clustering results are not spuriously capturing broader cluster-level, but not specialization-specific effects, as well as more diffuse (i.e., non-local) processes occurring at a national rather than cluster level.

Our baseline results echo prior studies. Clustered firms in the Canadian biotechnology industry are over eight times more innovative than non-clustered firms. Within clusters, the strongest effect is for firms located in a cluster strong in their technological specialization. These firms apply for patents at more than twice the rate of other specialization firms located in the same cluster, as well as same specialization firms located in other clusters that are not strong in the specialization. Thus, the more focused the innovative activity in a spatial area the greater the knowledge spillovers; the greatest gains from clustering are realized by locating within concentrations of firms with similar technological specializations. In addition, we find evidence that location within the cluster matters: firms face a decrease in R&D productivity when they are less central to other firms in the cluster.

Extending prior research, our findings indicate that the greater innovativeness of collocated firms of the same technological specialization may be attributed to their earning greater returns for R&D investments as a result of enhanced localized knowledge spillovers. In particular, we found that location in a cluster strong in a firm's technological specialization raises the productivity of its own R&D alliances and provides positive externalities gained from other firms' R&D alliances. In this manner, location serves as a partial substitute for access to information and ideas through formal employment relations. Our results also suggest the limits of agglomeration economies in the form of increased competition for skilled R&D employees within a cluster's strong technological specialization.

Taken together, our findings indicate that the benefits a firm derives from collocating with other firms in the same specialization depend importantly on the firm's ability to capitalize on available spillovers. Our results thus indicate the importance of absorptive capacity and of the characteristics of the learning environment within the cluster to generating positive externalities from clustering. As other firms in the cluster invest in R&D activity, the pool of new knowledge into which the firm can tap will be enhanced. Of course, low-level R&D investment equilibria in which the level of new knowledge is too limited to motivate individual firms to invest are also possible. Thus, at the cluster level, there is evidence of increasing returns to R&D investment.

Moreover, our results suggest that R&D alliances are a complement to geographic location: both provide access to knowledge and together they are mutually reinforcing. The most engaged firms will source knowledge both locally and through strategic alliances to the benefit of their inventive activity. For example, Owen-Smith and Powell (forthcoming) find that biotech firms located in Boston, perhaps the premier industrial cluster for this activity, engage in a large number of strategic alliances, many of them at long distance. Greater absorptive capacity is the result of exposure to a larger pool of ideas and therefore, firms also benefit from the strategic alliances of their neighbors. While Fontes (forthcoming) argues that strategic alliances may be used to compensate for geographic remoteness, our results suggest that R&D alliances generate higher returns when firms are located in clusters with firms working on similar applications.

Our findings have policy implications for both firms and jurisdictions. Many remote jurisdictions are investing resources in promoting the formation of biotech firms or attempting to recruit firms from other locations. While the aspiration to capture an economically important new industry is understandable, our results suggest that these firms will be less productive in these locations. By decreasing the natural tendency towards agglomeration, such efforts may operate to the determent of overall R&D productivity since an R&D investment in a remote firm will yield a lower return, all other things equal.

While our study reveals some new and more fine-grained dimensions of the benefits of geographic clustering in general, and the greater innovativeness of firms located in clusters strong in their own technology specialization in particular, much work remains to be done. Unfortunately, the literature has a limited understanding of the factors responsible for achieving critical and self-sustaining mass of firms within clusters. The logic of increasing returns suggests that only a few places will be able to sustain clusters in specific technological applications over the long run. Examining the development of an industry under a combined temporal-spatial-technological lens should help to address these larger questions.

Evidence is mounting that localized knowledge externalities or spillovers associated with industrial clustering are critical to innovation and the geographic distribution of economic value creation. Although we understand the properties and influences of clustering increasingly well, we need a better understanding of the processes and mechanisms underlying their innovation-enhancing properties. We hope our analysis of differences in the returns to a firm's own and other firms' R&D activities for firms located in clusters strong in their technological specialization relative to firms located in clusters that are not strong in their technological specialization provides grist for those keen to understand the black box of clustering effects.

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Tabel 1a. Descriptive Statistics for Geographic Clusters, 1991-2000

Prov	BC		AB1		AB2		SK		MB		ON1		ON2	
Variable	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Number of Firms in Cluster	69.57	5.50	17.71	2.50	11.71	1.38	14.57	1.40	6.00	1.41	115.00	17.09	11.57	1.90
Number of Firms in Same Specialization	5.29	9.03	5.86	1.21	3.86	2.04	8.57	0.79	3.43	1.27	27.57	21.90	2.43	1.72
Average Distance between Firms in Cluster (Km)	39.36	6.15	6.56	1.10	12.35	4.50	1.15	0.20	5.55	0.60	45.67	9.40	54.24	18.73
Number of University Labs	5.00	0.82	1.43	0.53	0.00	0.00	2.29	1.25	0.00	0.00	2.86	0.69	0.00	0.00
Patent Applications Last 5 Years	36.43	21.68	15.71	10.26	42.29	21.01	7.00	3.65	1.00	0.82	176.14	41.34	26.86	17.20
University Spinoff	9.14	3.34	2.71	1.25	2.29	1.11	0.00	0.00	0.00	0.00	2.57	0.98	1.43	0.79
Corporate Parent	5.71	1.60	4.00	1.53	1.00	0.00	4.86	0.69	2.00	0.58	31.14	8.34	2.29	1.38
Revenues (000,000)	771.56	1452.98	111.92	72.61	524.26	6.88	15.36	3.20	21.08	31.44	5112.05	1195.79	207.19	50.07
R&D Expenditures (000,000)	111.01	117.86	20.41	12.85	57.19	13.69	6.89	2.65	7.29	1.55	1056.50	275.89	14.55	1.44
R&D Employees	687.30	144.40	251.14	120.57	1156.71	51.95	79.57	11.96	57.57	30.17	2725.93	139.92	188.71	88.94
Financing (000,000)	55.45	62.66	14.99	17.05	9.81	9.65	4.75	5.88	0.00	0.00	78.62	75.45	2.14	5.24
IRAP Grants (000)	131.22	18.90	81.90	101.40	12.42	32.86	47.92	74.18	0.00	18.90	130.11	0.00	108.90	114.62
Upstream Alliances	80.71	26.95	17.29	1.60	5.29	4.99	23.43	3.55	3.14	1.77	123.14	28.59	17.86	6.44
Downstream Alliances	43.86	2.23	13.71	5.94	6.29	5.38	16.00	7.12	6.43	2.23	201.86	96.61	10.71	17.05
R&D Alliances	20.00	0.98	6.57	0.53	1.57	0.53	7.00	2.00	1.43	0.98	46.57	0.98	4.29	1.38
Prov	QC1		QC2		NB		PEI		NF		NS		Total	
Variable	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Number of Firms in Cluster	82.71	8.16	28.86	9.60	5.71	0.49	4.00	0.58	5.29	0.49	17.71	1.70	30.03	4.02
Number of Firms in Same Specialization	2.29	6.05	5.14	4.06	3.00	1.81	2.29	0.49	2.43	0.53	0.43	0.53	5.58	3.96
Average Distance between Firms in Cluster (Km)	42.79	22.00	37.29	30.99	11.82	9.40	28.46	22.00	83.19	9.40	43.85	9.40	31.71	11.07
Number of University Labs	1.14	0.38	0.00	0.00	0.00	0.00	0.00	0.00	3.29	0.49	1.29	1.46	1.33	0.43
Patent Applications Last 5 Years	68.29	31.49	11.71	9.66	0.43	0.53	1.14	1.07	0.00	6.43	1.14	0.90	29.86	12.77
University Spinoff	3.86	1.35	0.86	0.90	0.00	0.00	0.00	0.00	0.00	0.00	1.57	0.53	1.88	0.79
Corporate Parent	15.86	5.18	1.86	1.46	0.00	0.00	0.00	0.00	0.71	0.49	1.14	0.90	5.43	1.70
Revenues (000,000)	2982.21	727.86	210.34	25.25	23.91	2.05	14.36	2.86	1.81	0.41	94.74	124.21	776.21	284.28
R&D Expenditures (000,000)	194.24	51.26	22.18	17.00	0.89	0.56	0.91	0.76	3.31	1.52	10.26	1.95	115.82	38.38
R&D Employees	2382.86	485.98	369.86	218.40	22.00	6.45	19.43	5.86	23.29	2.06	127.43	16.05	622.45	101.75
Financing (000,000)	54.99	61.31	0.16	0.19	0.00	0.00	0.00	0.00	0.00	0.00	0.54	0.93	17.03	18.34
IRAP Grants (000)	98.63	0.00	0.00	114.62	0.00	0.00	0.00	0.00	0.00	0.00	56.21	0.00	51.33	36.57
Upstream Alliances	86.57	22.93	31.29	15.87	9.14	3.08	0.71	0.76	5.71	1.60	25.00	6.95	33.02	9.62
Downstream Alliances	69.43	3.24	28.43	17.05	1.14	0.38	3.86	3.24	0.57	17.05	28.71	23.98	33.15	15.50
R&D Alliances	27.00	1.38	5.14	1.38	1.43	0.98	0.29	1.38	4.86	1.38	4.71	0.95	10.07	1.14

Note the sample included 2439 yearly observations for firms located within a geographic cluster

Table 1b. Descriptive Statistics by Geographic Cluster Status

	Not in Strong Specialization		In Strong Specialization		Not in Cluster	
Variable	Mean	*S.D.*	Mean	*S.D.*	Mean	*S.D.*
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
ln(R&D Expenditures)	12.65	3.12	12.38	3.88	12.90	2.66
ln(R&D Employees)	2.07	1.14	2.11	1.31	1.91	1.10
ln(Revenues)	12.94	5.12	13.24	4.72	13.81	4.34
ln(Financing)	1.02	3.80	0.77	3.34	0.09	1.07
ln(IRAP Grants)	0.32	1.82	0.39	2.01	0.30	1.70
Upstream Alliances	1.21	1.94	1.19	1.89	0.84	2.70
Downsteam 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
Own Cluster Variables Same Specialization						
Number Firms in Same Specialization	8.96	7.43	22.07	20.36		
Number Same Specialization University Labs	0.20	0.43	0.23	0.57		
Same Specialization Patent Application Last 5 Years	10.61	27.81	17.40	30.50		
ln(Same Specialization R&D Expenditures)	13.00	6.37	16.51	3.04		
ln(Same Specialization R&D Employees)	3.65	2.16	5.16	1.87		
ln(Same Specialization Revenues)	14.39	7.17	18.02	3.86		
ln(Same Specialization Financing)	4.85	7.41	6.57	7.82		
ln(Same Specialization IRAP Grants)	1.57	3.83	3.11	5.06		
Same Specialization Upstream Alliances	9.18	10.67	21.72	17.73		
Same Specialization Downsteam Alliances	8.90	14.13	56.30	78.85		
Same Specialization R&D Alliances	3.16	4.45	9.69	9.85		
Own Cluster Variables Other Specializations						
Number Firms in Other Specialization	62.02	33.05	39.91	34.76		
Number Other Specialization University Labs	2.07	1.68	1.88	1.56		
Other Specialization Patent Application Last 5 Years	65.76	76.70	35.35	47.36		
ln(Other Specialization R&D Expenditures)	18.49	1.70	17.14	3.32		
ln(Other Specialization R&D Employees)	6.76	1.19	5.60	1.88		
ln(Other Specialization Revenues)	20.40	1.89	18.76	3.42		
ln(Other Specialization Financing)	13.77	6.53	10.18	7.73		
ln(Other Specialization IRAP Grants)	6.51	5.75	4.89	5.59		
Other Specialization Upstream Alliances	69.42	39.50	48.94	45.30		
Other Specialization Downsteam Alliances	74.82	80.21	49.47	55.25		
Other Specialization R&D Alliances	21.00	15.28	15.37	15.17		
Other Cluster Variables						
Number Firms in Same Specialization	37.60	24.85	57.33	18.14		
Number Same Specialization University Labs	1.28	1.06	1.44	0.60		
Same Specialization Patent Application Last 5 Years	38.27	59.36	56.67	72.76		
ln(Same Specialization R&D Expenditures)	17.50	2.91	18.54	1.00		
ln(Same Specialization R&D Employees)	6.05	1.49	6.86	0.65		
ln(Same Specialization Revenues)	19.55	2.80	20.30	1.18		
ln(Same Specialization Financing)	9.38	8.28	14.01	6.59		
ln(Same Specialization IRAP Grants)	5.68	5.76	6.37	5.94		
Same Specialization Upstream Alliances	43.21	27.43	61.63	22.38		
Same Specialization Downsteam Alliances	45.78	64.74	91.83	84.39		
Same Specialization R&D Alliances	13.72	12.12	22.45	12.21		

Note: The sample included 1930 yearly observatios for firms not in the strong specialization of their cluster, 508 yearly observations fro firms in the strong specialization of their cluster, and 132 yearly observations for firms 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	***
ln(R&D Expenditures)	-0.049	0.032	+
ln(R&D Employees)	0.465	0.079	***
ln(Revenues)	-0.045	0.018	**
ln(Financing)	-0.022	0.018	
ln(IRAP Grants)	-0.032	0.031	
Upstream Alliances	-0.047	0.042	
Downsteam Alliances	-0.078	0.029	**
R&D Alliances	-0.082	0.070	
Cluster Variable			
Located within a Geographic Cluster	2.134	0.708	**
Heckman Correction	-17.131	4.152	***
Constant	-3.008	0.819	***
Coverdispersion Parameter	4.183	0.521	***
Log-Likelihood	-920.26		

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

Table 3a. Negative Bionomial Regression Models of Patent Application Rates by Firms Located within a Geographic Cluster												
	Model 1			Model 2			Model 3			Model 4		
Firms Variables	*β*	*S.E.*		*β*	*S.E.*		*β*	*S.E.*		*β*	*S.E.*	
Age	0.001	*0.005*		0.001	*0.005*		-0.002	*0.005*		-0.001	*0.005*	
University Spinoff	0.897	*0.304*	**	1.056	*0.290*	***	1.007	*0.281*	***	0.700	*0.340*	*
Corporate Parent	0.500	*0.235*	*	0.342	*0.223*	+	0.244	*0.235*		0.392	*0.259*	+
Human Specialization	0.963	*0.186*	***	1.062	*0.225*	***	1.214	*0.242*	***	2.168	*0.562*	***
Patent Application Last 5 Years	0.145	*0.029*	***	0.134	*0.029*	***	0.132	*0.032*	***	0.111	*0.037*	**
ln(R&D Expenditures)	-0.052	*0.030*	*	-0.072	*0.029*	**	-0.071	*0.027*	**	-0.072	*0.026*	**
ln(R&D Employees)	0.491	*0.079*	***	0.537	*0.076*	***	0.515	*0.069*	***	0.480	*0.068*	***
ln(Revenues)	-0.038	*0.017*	*	-0.046	*0.016*	**	-0.037	*0.016*	**	-0.038	*0.016*	**
ln(Financing)	-0.008	*0.017*		-0.009	*0.016*		-0.005	*0.016*		-0.007	*0.016*	
ln(IRAP Grants)	0.031	*0.030*		0.026	*0.028*		0.028	*0.027*		0.024	*0.028*	
Upstream Alliances	-0.047	*0.042*		-0.053	*0.044*		-0.045	*0.043*		-0.045	*0.043*	
Downsteam Alliances	-0.049	*0.028*	*	-0.058	*0.030*	*	-0.077	*0.032*	**	-0.083	*0.032*	**
R&D Alliances	0.018	*0.069*		0.074	*0.069*		0.104	*0.070*	+	0.053	*0.072*	
Firm in Strong Specialization	-0.155	*0.214*		-0.189	*0.229*		-0.020	*0.269*		0.188	*0.277*	
Firm vs. Cluster Average Distance	-0.010	*0.004*	**	-0.010	*0.004*	**	-0.010	*0.004*	**	-0.011	*0.004*	**
Own Cluster Variables Same Specialization												
Number Firms in Same Specialization				0.061	*0.030*	*	0.031	*0.031*		0.005	*0.033*	
Number Same Specialization University Labs				0.180	*0.183*		0.387	*0.195*	*	0.426	*0.222*	*
Same Specialization Patent Application Last 5 Years				0.000	*0.003*		0.000	*0.003*		0.002	*0.004*	
ln(Same Specialization R&D Expenditures)				-0.002	*0.048*		-0.028	*0.047*		-0.013	*0.047*	
ln(Same Specialization R&D Employees)				-0.098	*0.114*		-0.067	*0.124*		-0.019	*0.118*	
ln(Same Specialization Revenues)				-0.003	*0.040*		0.016	*0.037*		0.004	*0.037*	
ln(Same Specialization Financing)				-0.031	*0.015*	*	-0.034	*0.014*	**	-0.028	*0.014*	*
ln(Same Specialization IRAP Grants)				0.039	*0.018*	*	0.039	*0.020*	*	0.051	*0.023*	*
Same Specialization Upstream Alliances				-0.060	*0.013*	***	-0.049	*0.014*	***	-0.039	*0.016*	**
Same Specialization Downsteam Alliances				-0.014	*0.006*	*	-0.010	*0.007*	+	-0.005	*0.007*	
Same Specialization R&D Alliances				0.110	*0.031*	***	0.091	*0.033*	**	0.052	*0.037*	+
Own Cluster Variables Other Specializations												
Number Firms in Other Specialization							-0.004	*0.010*		-0.015	*0.012*	
Number Other Specialization University Labs							-0.067	*0.074*		-0.086	*0.075*	
Other Specialization Patent Application Last 5 Years							-0.003	*0.002*	+	-0.002	*0.002*	
ln(Other Specialization R&D Expenditures)							-0.006	*0.174*		0.048	*0.170*	
ln(Other Specialization R&D Employees)							-0.079	*0.227*		0.004	*0.250*	
ln(Other Specialization Revenues)							0.170	*0.084*	*	0.164	*0.090*	*
ln(Other Specialization Financing)							-0.001	*0.017*		0.004	*0.017*	
ln(Other Specialization IRAP Grants)							0.030	*0.017*	*	0.034	*0.017*	*
Other Specialization Upstream Alliances							-0.006	*0.006*		-0.003	*0.006*	
Other Specialization Downsteam Alliances							0.003	*0.002*	+	0.003	*0.002*	+
Other Specialization R&D Alliances							0.020	*0.018*		0.019	*0.018*	
Other Cluster Variables												
Number Firms in Same Specialization										0.013	*0.014*	
Number Same Specialization University Labs										0.132	*0.123*	
Same Specialization Patent Application Last 5 Years										-0.003	*0.002*	+
ln(Same Specialization R&D Expenditures)										-0.051	*0.049*	
ln(Same Specialization R&D Employees)										-0.115	*0.169*	
ln(Same Specialization Revenues)										0.104	*0.055*	*
ln(Same Specialization Financing)										-0.011	*0.017*	
ln(Same Specialization IRAP Grants)										0.009	*0.017*	
Same Specialization Upstream Alliances										-0.014	*0.008*	*
Same Specialization Downsteam Alliances										-0.002	*0.003*	
Same Specialization R&D Alliances										-0.009	*0.022*	
Heckman Correction	-5.502	*2.015*	**	-5.464	*1.921*	**	-4.926	*2.094*	**	-7.957	*3.571*	*
Constant	-2.143	*0.445*	***	-1.734	*0.407*	***	-4.507	*2.343*	*	-5.587	*2.422*	**
Overdispersion Paramete	4.297	*0.521*	***	3.840	*0.462*	***	3.405	*0.418*	***	3.090	*0.416*	***
Log Likelihood	-911.17			-893.22			-881.42			-874.92		
Likelihood Ratio Test vs. Nested Model (*df*)				-35.901	*(11)*	***	-23.603	*(11)*	*	-12.991	*(11)*	

Note: +p<.10, *p<.05, **p<.01, ***p<.001. The Sample includes 2013 yearly observations for firms located within a geographic cluster.
All independent variables are lagged one year. Cluster variables are computed excluding the focal firm.

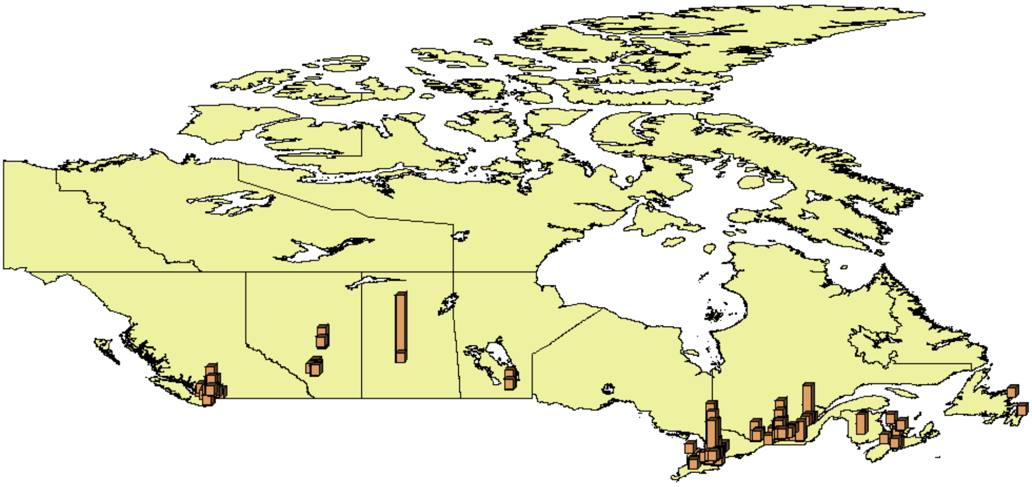
Table 3b. Negative Bionomial Regression Models of Patent Application Rates by Firms Located within a Geographic Cluster

	Model 5			Model 6			Model 7			Model 8		
Firms Variables	β	*S.E.*		β	*S.E.*		β	*S.E.*		β	*S.E.*	
Age	-0.002	*0.005*		-0.002	*0.005*		-0.002	*0.005*		-0.002	*0.005*	
University Spinoff	0.705	*0.345*	*	0.679	*0.336*	*	0.691	*0.342*	*	0.690	*0.341*	*
Corporate Parent	0.373	*0.259*	+	0.392	*0.259*	+	0.364	*0.260*	+	0.359	*0.259*	+
Human Specialization	2.159	*0.566*	***	2.361	*0.563*	***	2.353	*0.569*	***	2.332	*0.569*	***
Patent Application Last 5 Years	0.110	*0.038*	**	0.105	*0.037*	**	0.104	*0.037*	**	0.105	*0.037*	**
ln(R&D Expenditures)	-0.074	*0.030*	**	-0.077	*0.026*	**	-0.073	*0.030*	**	-0.070	*0.026*	**
ln(R&D Employees)	0.533	*0.082*	***	0.498	*0.071*	***	0.536	*0.083*	***	0.533	*0.081*	***
ln(Revenues)	-0.037	*0.016*	*	-0.035	*0.016*	*	-0.034	*0.016*	*	-0.034	*0.016*	*
ln(Financing)	-0.004	*0.016*		-0.007	*0.016*		-0.002	*0.016*		-0.002	*0.016*	
ln(IRAP Grants)	0.031	*0.028*		0.019	*0.028*		0.027	*0.029*		0.027	*0.028*	
Upstream Alliances	-0.042	*0.043*		-0.038	*0.043*		-0.034	*0.043*		-0.036	*0.043*	
Downsteam Alliances	-0.082	*0.032*	**	-0.082	*0.031*	**	-0.080	*0.031*	**	-0.080	*0.030*	**
R&D Alliances	-0.054	*0.096*		0.043	*0.073*		-0.080	*0.098*		-0.084	*0.099*	
Firm in Strong Specialization	0.295	*0.724*		0.990	*0.823*		1.386	*1.036*	+	0.931	*0.670*	+
Firm vs. Cluster Average Distance	-0.011	*0.004*	**	-0.011	*0.004*	**	-0.011	*0.004*	**	-0.011	*0.004*	**
Own Cluster Variables Same Specialization												
Number Firms in Same Specialization	0.004	*0.034*		0.008	*0.034*		0.004	*0.034*		0.004	*0.034*	
Number Same Specialization University Labs	0.400	*0.219*	*	0.370	*0.225*	*	0.343	*0.222*	+	0.352	*0.222*	+
Same Specialization Patent Application Last 5 Years	0.002	*0.004*		0.004	*0.004*		0.004	*0.004*		0.004	*0.004*	
ln(Same Specialization R&D Expenditures)	-0.018	*0.045*		-0.009	*0.047*		-0.015	*0.046*		-0.026	*0.043*	
ln(Same Specialization R&D Employees)	0.010	*0.115*		0.046	*0.122*		0.082	*0.121*		0.101	*0.121*	
ln(Same Specialization Revenues)	0.003	*0.035*		-0.003	*0.035*		-0.003	*0.034*		0.001	*0.034*	
ln(Same Specialization Financing)	-0.030	*0.014*	*	-0.031	*0.014*	*	-0.033	*0.014*	**	-0.033	*0.014*	**
ln(Same Specialization IRAP Grants)	0.047	*0.023*	*	0.049	*0.023*	*	0.046	*0.023*	*	0.044	*0.023*	*
Same Specialization Upstream Alliances	-0.037	*0.016*	**	-0.031	*0.016*	*	-0.028	*0.017*	*	-0.028	*0.017*	*
Same Specialization Downsteam Alliances	-0.006	*0.007*		-0.011	*0.008*	+	-0.012	*0.008*	+	-0.013	*0.008*	+
Same Specialization R&D Alliances	0.053	*0.038*	+	0.012	*0.040*		0.014	*0.041*		0.012	*0.041*	
Own Cluster Variables Other Specializations												
Number Firms in Other Specialization	-0.015	*0.012*		-0.016	*0.012*	+	-0.016	*0.012*	+	-0.015	*0.012*	
Number Other Specialization University Labs	-0.063	*0.074*		-0.095	*0.076*		-0.073	*0.076*		-0.072	*0.076*	
Other Specialization Patent Application Last 5 Years	-0.001	*0.002*		-0.001	*0.002*		-0.001	*0.002*		-0.001	*0.002*	
ln(Other Specialization R&D Expenditures)	0.025	*0.165*		0.028	*0.170*		0.000	*0.164*		-0.004	*0.165*	
ln(Other Specialization R&D Employees)	0.020	*0.247*		0.027	*0.247*		0.042	*0.244*		0.043	*0.244*	
ln(Other Specialization Revenues)	0.162	*0.089*	*	0.155	*0.089*	*	0.152	*0.090*	*	0.155	*0.090*	*
ln(Other Specialization Financing)	-0.001	*0.017*		0.006	*0.017*		0.002	*0.017*		0.001	*0.017*	
ln(Other Specialization IRAP Grants)	0.031	*0.017*	*	0.030	*0.017*	*	0.027	*0.017*	+	0.028	*0.017*	*
Other Specialization Upstream Alliances	-0.004	*0.006*		-0.004	*0.006*		-0.005	*0.006*		-0.005	*0.006*	
Other Specialization Downsteam Alliances	0.003	*0.002*		0.004	*0.002*	*	0.004	*0.002*	*	0.004	*0.002*	*
Other Specialization R&D Alliances	0.021	*0.018*		0.019	*0.019*		0.021	*0.019*		0.021	*0.019*	
Other Cluster Variables												
Number Firms in Same Specialization	0.012	*0.015*		0.013	*0.015*		0.012	*0.015*		0.012	*0.015*	
Number Same Specialization University Labs	0.116	*0.123*		0.119	*0.122*		0.101	*0.122*		0.101	*0.123*	
Same Specialization Patent Application Last 5 Years	-0.003	*0.002*	+	-0.004	*0.002*	*	-0.004	*0.002*	*	-0.004	*0.002*	*
ln(Same Specialization R&D Expenditures)	-0.053	*0.049*		-0.059	*0.049*		-0.061	*0.049*		-0.063	*0.049*	+
ln(Same Specialization R&D Employees)	-0.109	*0.171*		-0.153	*0.171*		-0.152	*0.172*		-0.151	*0.172*	
ln(Same Specialization Revenues)	0.108	*0.055*	*	0.125	*0.056*	*	0.131	*0.056*	**	0.135	*0.056*	**
ln(Same Specialization Financing)	-0.011	*0.017*		-0.012	*0.017*		-0.011	*0.017*		-0.011	*0.017*	
ln(Same Specialization IRAP Grants)	0.009	*0.017*		0.006	*0.017*		0.006	*0.017*		0.005	*0.017*	
Same Specialization Upstream Alliances	-0.013	*0.008*	*	-0.013	*0.008*	*	-0.012	*0.008*	+	-0.011	*0.008*	+
Same Specialization Downsteam Alliances	-0.002	*0.003*		-0.001	*0.003*		-0.001	*0.003*		-0.001	*0.003*	
Same Specialization R&D Alliances	-0.010	*0.022*		-0.014	*0.022*		-0.014	*0.022*		-0.014	*0.022*	
Strong Specialization Interactions												
ln(Firm R&D Expenditures)	0.033	*0.062*					0.002	*0.058*				
ln(Firm R&D Employees)	-0.335	*0.139*	**				-0.263	*0.137*	*	-0.248	*0.119*	*
Firm R&D Alliances	0.443	*0.148*	**				0.481	*0.148*	***	0.476	*0.149*	**
ln(Cluster Same Specialization R&D Expenditures)				-0.038	*0.087*		-0.056	*0.075*				
ln(Cluster Same Specialization R&D Employees)				-0.212	*0.246*		-0.180	*0.229*		-0.276	*0.172*	+
Cluster Same Specialization R&D Alliances				0.114	*0.058*	*	0.121	*0.058*	*	0.124	*0.058*	*
Heckman Correction	-7.626	*3.621*	*	-8.646	3.548	**	-8.245	3.569	**	-8.201	3.562	**
Constant	-5.432	*2.369*	*	-5.237	*2.470*		-5.041	*2.394*	*	-5.094	*2.408*	*
Overdispersion Paramete	3.009	*0.405*	***	3.011	*0.405*	***	2.918	*0.397*	***	2.925	*0.397*	***
Log Likelihood	-871.77			-872.79			-869.43			-869.62		
Likelihood Ratio Test vs. Nested Model (*df*)	-6.30	*(3)*	+	-4.27	*(3)*		-10.98	*(6)*	+	-10.61	*(4)*	*

Note: +p<.10, *p<.05, **p<.01, ***p<.001. The Sample includes 2013 yearly observations for firms located within a geographic cluster.
All independent variables are lagged one year. Cluster variables are computed excluding the focal firm.

Figure 1. Density of Firms located within Geographic Clusters of Biotechnology Firms in Canada, 1991 and 2000

1991



2000

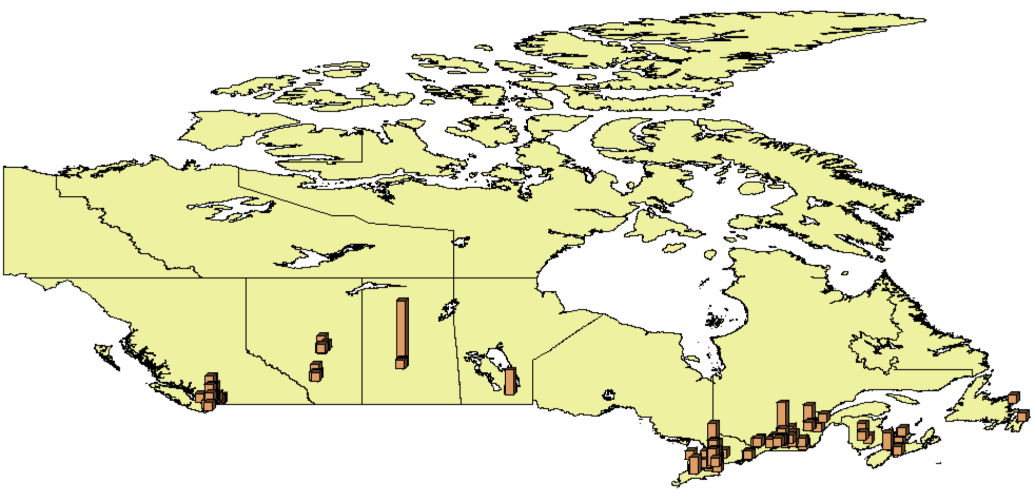


Figure 2. Concentration of Technological Specialization Activity by Cluster.

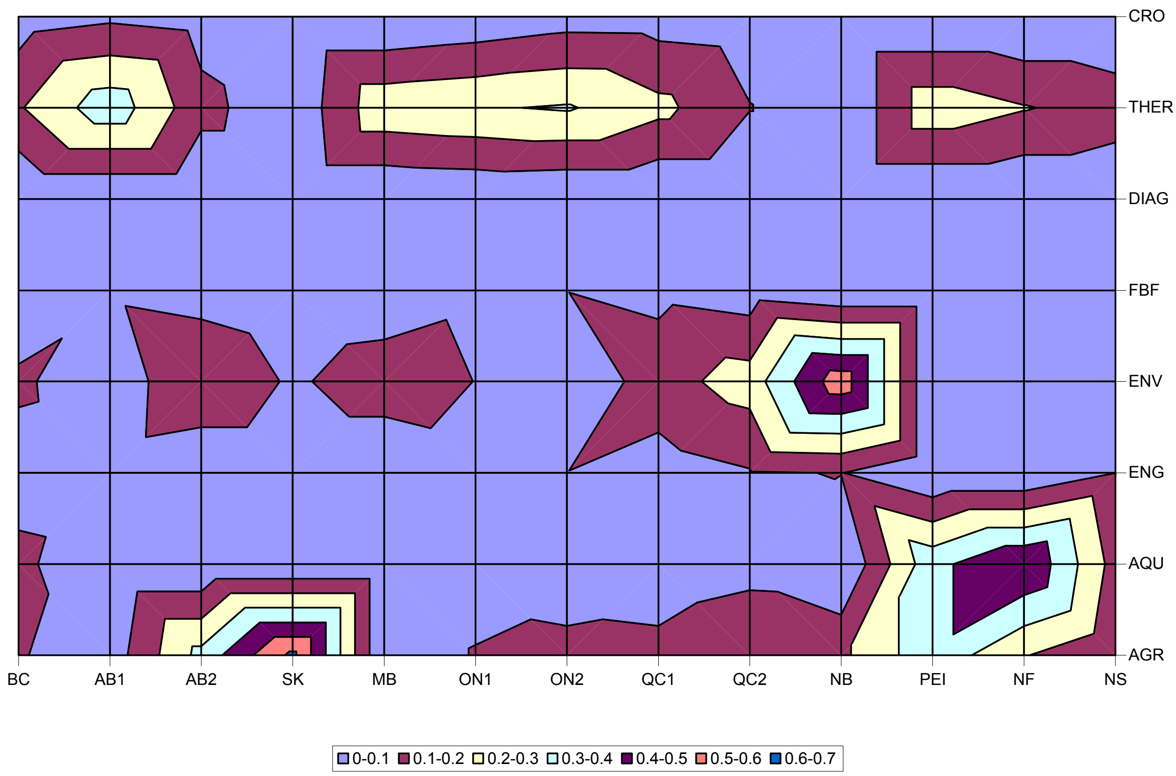
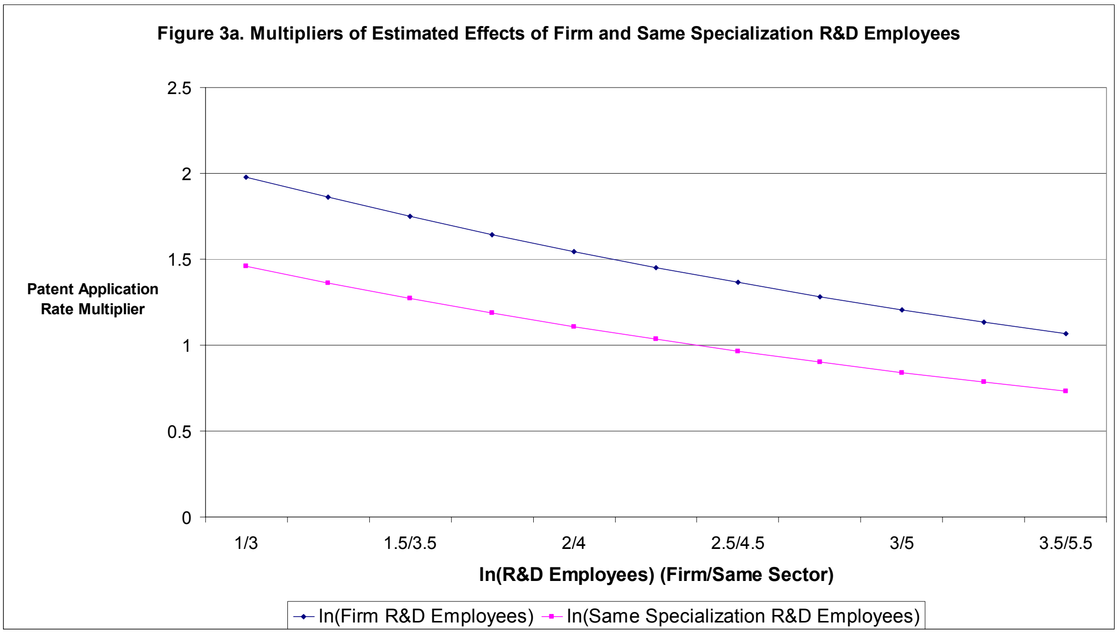


Figure 3. Strong Technology Specialization Interaction Multipliers



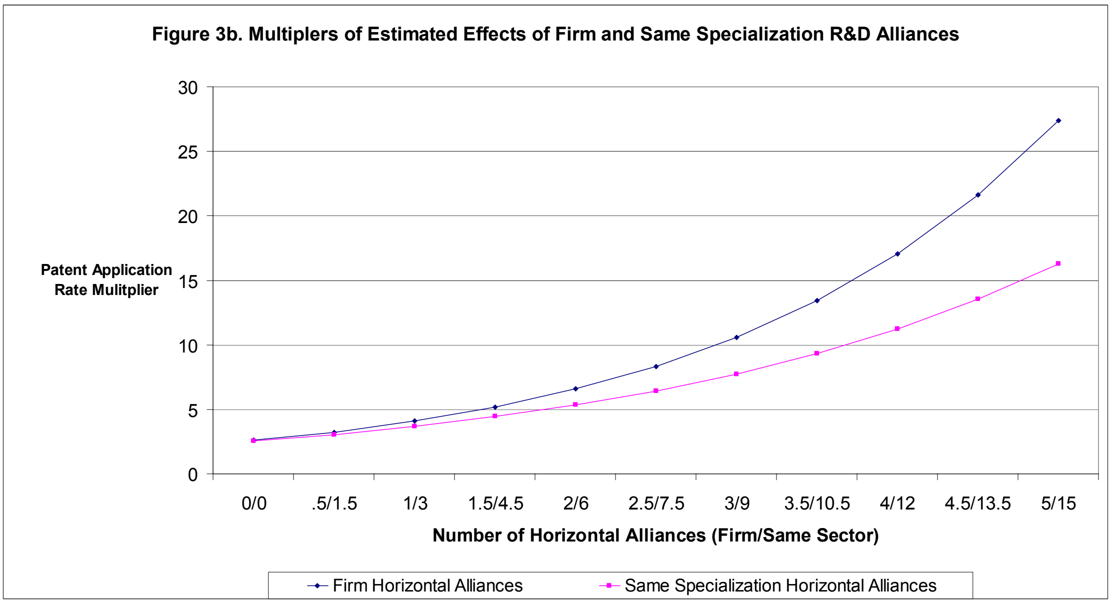


Table A1: Descriptive Statistics and Bivariate Correlations, Firm in Clusters

	Firms Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	Age																								
2	University Spinoff	-0.178																							
3	Corporate Parent	0.210	-0.108																						
4	Human Specialization	-0.166	0.164	0.068																					
5	Patent Application Last 5 Years	0.116	0.067	0.107	0.138																				
6	ln(R&D Expenditures)	0.138	0.011	0.036	0.093	0.163																			
7	ln(R&D Employees)	0.212	0.094	0.110	0.166	0.295	0.478																		
8	ln(Revenues)	0.364	-0.174	0.047	-0.212	0.071	0.231	0.158																	
9	ln(Financing)	-0.114	0.240	-0.084	0.184	0.153	0.013	0.118	-0.154																
10	ln(IRAP Grants)	-0.109	0.196	-0.028	0.017	0.025	-0.023	0.034	-0.084	0.007															
11	Upstream Alliances	-0.026	0.151	-0.057	-0.044	0.000	0.031	0.049	-0.119	0.083	0.078														
12	Downsteam Alliances	0.069	-0.025	0.094	0.188	0.098	0.110	0.127	0.109	0.038	-0.014	0.021													
13	R&D Alliances	-0.001	0.028	0.111	0.124	0.081	0.131	0.135	0.049	0.076	0.070	0.067	0.070												
14	Firm in Strong Specialization	-0.066	0.006	0.084	0.209	-0.014	-0.036	0.018	0.004	-0.053	0.015	-0.006	0.082	0.075											
15	Firm vs. Cluster Average Distance	-0.014	-0.023	0.007	-0.196	-0.074	-0.010	-0.121	-0.008	-0.061	0.020	0.076	-0.073	0.022	-0.030										
	Own Cluster Variables Same Specialization																								
16	Number Firms in Same Specialization	-0.063	-0.028	0.074	0.549	0.046	0.097	0.071	-0.038	0.052	-0.057	-0.039	0.161	0.127	0.389	-0.059									
17	Number Same Specialization University Labs	-0.092	0.115	-0.030	0.081	-0.027	-0.046	-0.015	-0.087	0.101	0.005	0.050	-0.052	-0.003	0.041	-0.038	-0.030								
18	Same Specialization Patent Application Last 5 Years	-0.024	-0.003	0.065	0.444	0.125	0.067	0.079	-0.098	0.129	-0.037	-0.017	0.051	0.074	0.078	-0.004	0.411	-0.069							
19	ln(Same Specialization R&D Expenditures)	-0.032	-0.036	0.016	0.318	0.017	0.054	0.020	-0.016	0.055	-0.061	-0.074	0.038	0.054	0.224	0.033	0.558	0.164	0.328						
20	ln(Same Specialization R&D Employees)	-0.060	0.003	0.047	0.476	0.045	0.084	0.069	-0.055	0.072	-0.051	-0.043	0.069	0.097	0.261	-0.009	0.733	0.078	0.456	0.870					
21	ln(Same Specialization Revenues)	0.023	-0.083	0.017	0.198	-0.004	0.080	0.008	0.054	0.020	-0.080	-0.070	0.053	0.065	0.214	0.044	0.538	0.074	0.281	0.920	0.821				
22	ln(Same Specialization Financing)	-0.112	0.087	-0.004	0.607	0.104	0.073	0.083	-0.160	0.186	-0.030	0.000	0.060	0.060	0.074	-0.098	0.539	0.205	0.533	0.440	0.561	0.348			
23	ln(Same Specialization IRAP Grants)	-0.067	0.041	0.052	0.288	-0.020	0.004	0.025	-0.081	0.016	0.046	-0.008	0.047	0.041	0.158	-0.043	0.321	0.065	0.038	0.261	0.319	0.210	0.201		
24	Same Specialization Upstream Alliances	-0.071	0.047	0.078	0.564	0.060	0.072	0.085	-0.068	0.099	-0.034	-0.011	0.131	0.130	0.337	-0.102	0.855	0.056	0.475	0.547	0.706	0.499	0.597	0.398	
25	Same Specialization Downsteam Alliances	-0.056	-0.054	0.081	0.431	0.004	0.057	0.036	-0.017	-0.002	-0.046	-0.032	0.156	0.106	0.424	-0.064	0.901	-0.102	0.222	0.351	0.493	0.342	0.341	0.228	0.699
26	Same Specialization R&D Alliances	-0.058	-0.042	0.108	0.549	0.068	0.077	0.079	-0.046	0.043	-0.045	-0.018	0.151	0.075	0.365	-0.085	0.909	-0.096	0.487	0.486	0.671	0.463	0.505	0.347	0.838
	Own Cluster Variables Other Specializations																								
27	Number Firms in Other Specialization	0.157	-0.100	0.063	0.041	0.022	0.115	0.060	0.076	0.040	-0.112	-0.049	0.028	0.013	-0.272	0.050	0.381	-0.053	0.216	0.392	0.434	0.414	0.260	0.104	0.320
28	Number Other Specialization University Labs	-0.035	0.040	-0.018	0.115	-0.026	0.036	-0.054	-0.019	0.056	-0.039	-0.026	-0.007	0.040	-0.051	0.016	0.288	0.094	0.114	0.187	0.220	0.161	0.268	0.215	0.286
29	Other Specialization Patent Application Last 5 Years	0.196	-0.088	0.060	-0.060	0.059	0.050	0.028	0.108	0.032	-0.063	-0.072	0.014	-0.029	-0.177	0.068	0.129	-0.060	0.165	0.228	0.227	0.260	0.115	-0.056	0.072
30	ln(Other Specialization R&D Expenditures)	0.110	-0.072	0.056	0.150	0.073	0.107	0.062	0.043	0.063	-0.106	-0.093	0.055	0.015	-0.263	0.034	0.462	-0.137	0.305	0.370	0.444	0.384	0.313	0.105	0.360
31	ln(Other Specialization R&D Employees)	0.127	-0.059	0.026	0.097	0.071	0.105	0.066	0.053	0.073	-0.129	-0.087	0.019	-0.006	-0.346	0.048	0.382	-0.176	0.245	0.387	0.435	0.413	0.289	0.083	0.316
32	ln(Other Specialization Revenues)	0.102	-0.038	0.035	0.152	0.083	0.116	0.097	0.029	0.081	-0.094	-0.073	0.045	0.000	-0.299	0.039	0.402	-0.173	0.284	0.340	0.416	0.346	0.305	0.091	0.321
33	ln(Other Specialization Financing)	0.111	-0.042	0.029	0.045	0.048	0.076	0.052	0.052	0.073	-0.081	-0.044	-0.001	0.002	-0.220	0.056	0.333	0.020	0.207	0.388	0.425	0.393	0.296	0.116	0.348
34	ln(Other Specialization IRAP Grants)	0.039	-0.036	0.028	0.025	0.038	0.019	-0.018	-0.041	0.025	0.011	-0.024	0.067	-0.023	-0.128	0.012	0.121	-0.075	0.195	0.125	0.120	0.110	0.127	0.241	0.146
35	Other Specialization Upstream Alliances	0.135	-0.097	0.050	0.022	0.014	0.101	0.038	0.056	0.059	-0.101	-0.050	0.034	0.006	-0.224	0.059	0.371	-0.052	0.161	0.361	0.385	0.375	0.274	0.108	0.308
36	Other Specialization Downsteam Alliances	0.135	-0.121	0.092	-0.023	0.009	0.097	0.035	0.067	-0.008	-0.066	-0.010	0.035	0.025	-0.147	0.037	0.293	-0.078	0.150	0.256	0.281	0.275	0.133	0.033	0.220
37	Other Specialization R&D Alliances	0.159	-0.105	0.077	-0.007	0.003	0.101	0.040	0.074	0.011	-0.094	-0.038	0.044	0.001	-0.152	0.052	0.340	-0.046	0.140	0.321	0.349	0.342	0.196	0.078	0.271
	Other Cluster Variables																								
38	Number Firms in Same Specialization	-0.168	0.064	0.035	0.654	0.019	-0.010	0.020	-0.116	0.067	0.006	-0.058	0.123	0.079	0.316	-0.157	0.353	0.116	0.150	0.337	0.391	0.273	0.323	0.234	0.374
39	Number Same Specialization University Labs	-0.069	-0.064	-0.009	-0.015	0.023	0.006	-0.040	-0.043	0.006	-0.043	-0.026	-0.075	-0.031	0.070	0.109	0.095	-0.133	0.210	0.222	0.193	0.221	0.087	-0.131	0.095
40	Same Specialization Patent Application Last 5 Years	-0.145	0.215	-0.011	0.660	0.129	0.016	0.115	-0.227	0.203	0.039	0.006	0.039	0.012	0.097	-0.124	0.149	0.179	0.322	0.190	0.243	0.054	0.438	0.062	0.304
41	ln(Same Specialization R&D Expenditures)	-0.071	0.042	-0.006	0.332	0.016	-0.001	-0.002	-0.078	0.032	-0.029	-0.005	0.034	0.072	0.153	-0.053	0.218	0.065	0.107	0.345	0.345	0.323	0.218	0.121	0.241
42	ln(Same Specialization R&D Employees)	-0.121	0.063	0.057	0.508	0.027	-0.006	0.021	-0.126	0.081	-0.028	-0.026	0.079	0.070	0.223	-0.124	0.328	0.158	0.164	0.396	0.416	0.327	0.351	0.202	0.362
43	ln(Same Specialization Revenues)	-0.065	0.005	-0.012	0.161	-0.046	-0.020	-0.044	-0.017	-0.023	-0.027	-0.023	0.022	0.056	0.121	-0.029	0.113	0.106	-0.100	0.326	0.260	0.306	0.088	0.108	0.126
44	ln(Same Specialization Financing)	-0.143	0.082	0.048	0.674	0.094	0.032	0.110	-0.165	0.158	-0.012	-0.055	0.118	0.076	0.200	-0.132	0.396	0.122	0.328	0.341	0.426	0.246	0.455	0.159	0.414
45	ln(Same Specialization IRAP Grants)	-0.076	0.016	0.032	0.276	-0.008	0.023	-0.003	-0.078	0.010	0.057	-0.002	0.088	0.037	0.060	-0.012	0.179	0.018	0.091	0.207	0.229	0.170	0.168	0.331	0.232
46	Same Specialization Upstream Alliances	-0.152	0.056	0.040	0.549	0.063	-0.023	0.014	-0.133	0.079	0.025	-0.060	0.093	0.031	0.273	-0.079	0.220	0.069	0.258	0.313	0.330	0.237	0.311	0.181	0.275
47	Same Specialization Downsteam Alliances	-0.141	0.078	0.047	0.619	-0.003	-0.003	0.050	-0.099	0.056	0.044	-0.039	0.183	0.114	0.247	-0.172	0.326	0.019	0.047	0.188	0.270	0.143	0.241	0.304	0.333
48	Same Specialization R&D Alliances	-0.169	0.091	0.027	0.712	0.000	0.006	0.037	-0.122	0.066	0.027	-0.069	0.189	0.074	0.263	-0.177	0.344	0.077	0.039	0.278	0.332	0.209	0.304	0.296	0.330
	Own Cluster Variables Same Specialization		25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47
26	Same Specialization R&D Alliances		0.824																						
	Own Cluster Variables Other Specializations																								
27	Number Firms in Other Specialization		0.246	0.325																					
28	Number Other Specialization University Labs		0.183	0.221	0.450																				
29	Other Specialization Patent Application Last 5 Years		0.086	0.068	0.565	0.141																			
30	ln(Other Specialization R&D Expenditures)		0.352	0.416	0.845	0.341	0.595																		
31	ln(Other Specialization R&D Employees)		0.247	0.328	0.862	0.244	0.566	0.895																	
32	ln(Other Specialization Revenues)		0.289	0.352	0.797	0.196	0.531	0.907	0.889																
33	ln(Other Specialization Financing)		0.188	0.270	0.707	0.461	0.496	0.681	0.729	0.620															
34	ln(Other Specialization IRAP Grants)		0.063	0.117	0.335	0.262	0.331	0.330	0.289	0.260	0.290														
35	Other Specialization Upstream Alliances		0.274	0.327	0.910	0.474	0.513	0.788	0.781	0.725	0.703	0.371													
36	Other Specialization Downsteam Alliances		0.229	0.282	0.811	0.251	0.377	0.656	0.589	0.600	0.404	0.275	0.765												
37	Other Specialization R&D Alliances		0.259	0.289	0.915	0.355	0.532	0.773	0.744	0.697	0.588	0.371	0.891	0.866											
	Other Cluster Variables																								
38	Number Firms in Same Specialization		0.254	0.313	-0.233	-0.081	-0.199	-0.157	-0.151	-0.130	-0.165	-0.104	-0.248	-0.216	-0.234										
39	Number Same Specialization University Labs		-0.025	0.056	-0.051	-0.023	0.002	-0.027	-0.020	-0.025	-0.028	-0.056	-0.062	-0.043	-0.077	0.201									
40	Same Specialization Patent Application Last 5 Years		0.043	0.104	-0.127	0.032	-0.040	-0.041	-0.047	-0.024	0.015	-0.018	-0.098	-0.202	-0.143	0.470	0.119								
41	ln(Same Specialization R&D Expenditures)		0.097	0.192	-0.184	-0.075	-0.144	-0.125	-0.076	-0.094	-0.079	-0.028	-0.179	-0.195	-0.207	0.576	0.251	0.305							
42	ln(Same Specialization R&D Employees)		0.218	0.283	-0.177	-0.030	-0.115	-0.093	-0.102	-0.072	-0.080	0.000	-0.154	-0.161	-0.178	0.770	0.201	0.419	0.774						
43	ln(Same Specialization Revenues)		0.040	0.066	-0.197	-0.103	-0.137	-0.170	-0.113	-0.132	-0.090	-0.104	-0.186	-0.197	-0.216	0.538	0.131	0.152	0.820	0.738					
44	ln(Same Specialization Financing)		0.297	0.383	-0.062	0.065	0.026	0.073	0.006	0.044	0.047	0.090	-0.021	-0.104	-0.082	0.597	0.209	0.529	0.429	0.569	0.302				
45	ln(Same Specialization IRAP Grants)		0.111	0.220	0.011	-0.011	-0.033	0.049	0.027	0.056	0.023	0.270	0.063	0.024	0.077	0.345	0.008	0.124	0.201	0.335	0.177	0.169			
46	Same Specialization Upstream Alliances		0.119	0.173	-0.243	-0.090	-0.084	-0.127	-0.145	-0.109	-0.124	0.027	-0.224	-0.241	-0.219	0.855	0.273	0.600	0.505	0.691	0.439	0.556	0.375		
47	Same Specialization Downsteam Alliances		0.324	0.348	-0.116	-0.032	-0.198	-0.047	-0.038	-0.014	-0.089	-0.061	-0.139	-0.130	-0.130	0.784	-0.124	0.254	0.335	0.480	0.313	0.449	0.305	0.585	
48	Same Specialization R&D Alliances		0.313	0.299	-0.175	-0.037	-0.142	-0.082	-0.087	-0.051	-0.116	-0.043	-0.174	-0.207	-0.184	0.892	-0.035	0.426	0.462	0.644	0.445	0.544	0.371	0.737	0.868

Note: The sample included 2013 yearly observations for firms located within a geographic cluster