Inventive and Uninventive Clusters:

The Case of Canadian Biotechnology[1]

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Abstract

We examine factors influencing the relative productivity of different geographic locations. Our analysis of the Canadian biotechnology industry during the 1990s reveals that inventive and uninventive locations are distinguishable within small geographic areas corresponding to roughly 7,000 postal addresses. Inventive locations exhibit greater resource scale and technological focus, as well as greater emphasis on R&D investment and public and private collaboration. Comparison of inventive locations across three major metropolitan areas – Vancouver, Toronto and Montreal – indicates, however, that inventive locations vary in their emphasis on technological scale and focus relative to collaboration, and thus that location advantages can develop in distinctive ways.

Keywords: Location advantage, industrial clustering, knowledge spillovers

Introduction

The idea that location can provide an advantage to economic activity is central to theorizing in the new economic geography, which suggests that firms' inventive productivity is enhanced by proximity, and emphasizes the importance of resources that are external to the firm but internal to the location. Many factors including access to specialized labor, an abundance of intermediate suppliers, or proximity to markets are associated with spatial agglomeration economies; however, because of their relevance to growth theory and the economics of human capital, knowledge spillovers represent an important micro-foundation (Rosenthal and Strange 2003).

Although evidence is mounting that geographic concentration contributes to firms' inventiveness (Audretsch and Feldman 1996; Baptista and Swann 1998; Aharonson et al. 2007; Beaudry 2001; Beaudry and Breschi 2003; Swann et al. 1998), and that this explains the tendency of inventive activity to cluster, beyond variation in the extent of geographic and technological concentration our understanding of factors influencing the relative productivity of different clusters remains limited. The concept of industrial clusters extends beyond clustering in geographic and technological space, however. The productivity of a local environment depends not only on the scale of available inputs, but also how such inputs are organized and interact. For a given technology and place, local industrial organization – the demography, character, and propensity to work together of colocated firms – also influences the quality and intensity of location benefits (Porter 1990; Saxenian 1994). For a location to enhance innovation, its industrial organization must facilitate the transfer of knowledge among the individuals and firms comprising it.

Moreover, while there is a consensus about the importance of firm competencies and affiliations in the production and transmission of knowledge (Nelson and Winter 1982; Dosi et al. 1988; Powell et al. 1996; Teece et al. 1997), we know little about how firms' investments in these activities influence clustering benefits (Mariani, 2004). The advantages of clustering are certainly not uniform, however, and differences in firms' investments in internal and collaborative R&D activities likely influence the relative benefits they derive (Owen-Smith and Powell 2004). Investments in internal and collaborative capabilities not only affect a firm's ability to develop new knowledge, they also contribute to its absorptive capacity – the ability to recognize and exploit relevant external knowledge (Cohen and Levinthal 1990; Powell et al. 1996). The ability of firms to benefit from location is thus a function of their capacity to absorb local knowledge spillovers, interacting with characteristics of the local knowledge pool (e.g., scale, technical focus) and industrial organization (e.g., the degree of collaboration and knowledge sharing among local firms).

In this paper, we exploit a unique, longitudinal dataset on the Canadian biotechnology industry during the 1990s to examine factors influencing the relative productivity of locations directly. The dataset contains detailed information on each firm, including its location, technological focus, internal and collaborative R&D activities, patenting and financing. Our analysis unfolds in three phases. First we examine the identity and geographic scale of inventive and uninventive locations empirically. Consistent with other recent research on knowledge spillovers (e.g., Aharonson et al. 2007; Globerman, Shapiro and Vining 2005; Rosenthal and Strange 2003; Stuart and Sorenson 2003; Wallsten 2001), we find that inventive and uninventive locations are distinguishable within small geographic areas corresponding to Forward Sortation Areas (FSAs) covering roughly 7,000 postal addresses. Second, we examine the character of inventive and uninventive locations and the capabilities of firms comprising them. Inventive locations exhibit greater resource scale and technological focus, as well as greater emphasis on R&D investment and public and private collaboration. Uninventive firms operating in inventive locations enjoy more limited internal and external resources than neighboring inventive firms, but are still advantaged relative to firms in uninventive locations. Third, we examine the location of inventive locations, as well as variation in their characteristics. A comparison of inventive locations within Canada's three largest metropolitan areas – Vancouver, Toronto and Montreal – reveals variation in emphasis on technological scale and focus relative to collaboration, suggesting that location advantages can develop in multiple ways.

Inventiveness of Firms and Locations

Although there is consensus about the importance of firm competencies (e.g., learning processes, the capabilities to coordinate and integrate internal activities, and the ability to modify strategies and competencies when external conditions change) and affiliations (e.g., R&D alliances, university alliances) in the production and transmission of knowledge (Nelson and Winter 1982; Dosi et al. 1988; Powell et al. 1996; Teece et al. 1997; Zucker et al. 1998a, 1998b; Belderbos, Carree, and Lokshin 2004), research increasingly emphasizes a third factor in the production and transmission of knowledge: the geographical cluster.

Research on clusters emphasizes the role of local infrastructure for innovation and growth (Marshall 1920; Rohmer 1986; Porter 1998) and advances localized knowledge spillovers among neighboring firms as a source of increasing returns from investment in R&D (Jaffe 1986; Jaffe et al. 1993). By colocating, firms and individuals can communicate among themselves and monitor each other more easily. Proximity is particularly important when informal, uncodified knowledge is involved in the production of new knowledge, and when knowledge transfer relies on practice and learning-by-doing. As a result, skill- and R&D-intensive industries should tend to benefit more from colocation (Audretsch and Feldman 1996; Breschi 1999), as should those in early compared to mature or declining industry life cycle stages (Klepper 1996). Consistent with these ideas, Mariani (2004) shows that in biotechnology, a young, science-based industry, the main drivers of innovation are regional technological characteristics and focus, not individual firms' R&D intensity.

The concept of industrial clusters extends beyond concentration in geographic and technological space, however. For a given technology and place, the propensity of firms to work together and share knowledge can influence the quality and intensity of externalities (Porter 1990; Saxenian 1994). The productivity of a local environment depends not only on the scale and focus of available inputs, but also on the way in which they are organized and interact. In biotechnology, for example, Powell et al. (1996) showed that the locus of innovation is the network of firms, rather than individual firms, and Zucker et al. (1998a, 1998b) showed that access to university research through working relationships between firms and top academic scientists enhanced firms' R&D productivity. Such spillovers are not unintentional, however; they require direct collaboration (Arora et al. 2001). What role does firms' propensity to invest in such direct collaboration play in shaping the relative influence of firm and location as drivers of innovation?

We lack a clear understanding not only of how firms' investments in collaborative capabilities influence the degree to which they benefit from clustering, but also their investments in internal capabilities. Yet, firms' investments in internal capabilities not only affect their ability to develop new knowledge internally; they also contribute to their absorptive capacity – the ability to recognize and exploit relevant external knowledge (Cohen and Levinthal 1990).

In sum, the inventiveness of firms is likely a function of their internal and collaborative capabilities interacting with technical developments and market opportunities emerging in the external environment. Unfortunately, the roles of the firm and location in the invention process have typically been studied separately. The present paper examines them jointly. As a young, research-intensive and prolifically patenting industry, biotechnology seems a suitable empirical setting in which to examine their joint influence on firms' inventive productivity.

Data

Our data cover 675 biotechnology firms operating in Canada at any time between January 1991 and

December 2000. The sample includes 204 startups founded during the period (of which 69 ceased operations by December 2000) and 471 incumbents founded prior to 1991 (of which 195 ceased operations by December 2000). The data were compiled based on *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, technological focus, products, growth, performance, alliances, and location. We cross-checked this information with *The Canadian Biotechnology Handbook* (1991, 1993, 1995, 1996, 1997, 1998, 1999), which lists information for a more restrictive set of firms dedicated solely to biotechnology.

Data on financing 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 were assembled 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.

Methods

We examine the effects of location on biotechnology firms' inventive productivity, indexed by patent application rates (e.g., Owen-Smith and Powell 2004), to empirically identify the geographic scope and relative inventive productivity of locations.[3] Because patents vary greatly in their importance and value, a concern with studying patenting rates is that they are not informative about innovative output or commercial significance (Trajtenberg 1990). However, our interest is in patents as an

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

[3] We use patent application dates to determine the timing of inventions to ensure that firms' (lagged) internal and external resources are available during the invention process. If we use patent grant dates, which can follow application dates by several years, it is possible that firms' resources were acquired after the invention process concluded but before a patent is granted.

indicator of invention, rather than socioeconomic value. That said, in biotechnology, there is little of commercial value that is not patented, and patents do typically afford effective protection (Lerner and Merges 1998). As a result, patents are integral to creating economic value, and a necessary condition for creating it. Thus we feel it meaningful to identify inventive and uninventive locations based on patenting rates for this industry.

Estimation. For the analysis, we pooled annual observations for each firm, estimating a single model on the pooled cross-sections. Each firm enters the sample either in 1991 or the year of its founding and remains in the sample either until the end of 2000 or the year in which it ceases operations. Each firm thus contributes a number of observations to the sample equal to the number of years it was in operation during the years 1991 through 2000.

Because the dependent variable in this analysis, a firm's yearly number of patent applications, 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 (Coleman 1981). A Poisson process provides a natural baseline model for such processes (Hausman, Hall and Griliches 1984), that is used widely in analyses of patenting (Henderson and Cockburn 1996; Rosenkopf and Nerkar 2001; Mowery, Sampat and Ziedonis 2002). The basic Poisson model for count data is:

$$Pr(Y_t = y) = exp\ \lambda(x_i)[\lambda(x_i)y/y!] \quad (1)$$

where both the probability of a given number of events in an interval, $Pr(Y_t = y)$, and the variance of the number of events in each interval equal the rate, $\lambda(x_i)$. Thus, the Poisson model makes the strong assumption that there is no heterogeneity in the sample. However, for count data, the variance often exceeds the mean, and such overdispersion causes the standard errors of parameters to be underestimated, overstating levels of statistical significance. 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:

$$\lambda_t = exp(\pi' x_i)\varepsilon_t \tag{2}$$

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:

$$Var(Y_t) = E(Y_t)[1+\alpha E(Y_t)] \tag{3}$$

We implemented the model using a conservative Huber/White/sandwich robust variance estimator that adjusts for within-firm correlation to account for the potential non-independence of repeated observations on each firm.

Firm-Effects Specification. The baseline model controls for firm-specific factors likely to influence the inventiveness of biotechnology firms, which, if uncontrolled, may lead to spurious location effects (e.g., reflecting areas where more competent firms locate). With firm effects controlled, location effects indicate the relative inventiveness of locations after accounting for variation in the attributes of their respective firms. In our models, a location contributes positively to inventiveness if firms residing within it are more inventive than their attributes predict. All firm-level controls are updated annually and lagged one year in model estimation.[4]

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 each firm's technological competence using a count of its number of patent applications during the last 5 years. For firms already operating in 1991, we used information on patent applications for 1986-90 to compute counts for 1991-95. This 5-year count measure follows windows in prior research (Baum et al. 2000; Podolny and Stuart 1995; Podolny et al. 1996). Including the lagged patent application count to

[4] Information on firm attributes is nearly complete; in a small number of cases where data for a particular attribute is missing for a given firm we use linear interpolation to estimate its value.

predict current applications helps account for the possibility that our empirical models suffer from specification bias due to unobserved heterogeneity, permitting greater confidence when inferring causal relationships between independent and dependent variables (Heckman and Borjas 1980; Jacobson 1990).

A firm's internal and external R&D activities may also affect its inventive output (Powell et al. 1996). Therefore, we also controlled for each firm's R&D investments and activities using four 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), 3) number of R&D alliances with other biotechnology firms, and 4) number of alliances with universities.[5]

In addition to R&D alliances with other biotechnology firms and universities, biotechnology firms also establish downstream alliances for manufacturing and distribution with pharmaceutical firms, chemical firms, and marketing firms that link them to sources of complementary assets including distribution channels, marketing expertise and production facilities, as well as financing (Kogut, Shan and Walker 1992). They also form upstream alliances for basic research with research institutes, government labs, and hospitals that, like university alliances, link biotechnology firms to sources of research know-how and technological expertise critical to the discovery and patenting of new products or processes (Argyres and Liebeskind 1998). To control for possible effects of these alliances on inventive output, we include separate yearly counts of each firm's number of upstream and downstream alliances. Additionally, 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 academic resources, or benefit from university funds dedicated to technology transfer.

A firm's access to financial capital may also affect its ability to patent. For independent firms,

[5] Although we know locations for some firms' alliance partners, and know they are often distant, too much of this information is missing to incorporate partner locations in the empirical analysis.

venture capital and private placement investments are vital to supporting inventive activity. Another capital source for Canadian biotechnology firms are 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 advancing unproven technology. Therefore, we controlled for the yearly total financing and IRAP grants received by a firm (both in 1991 Canadian dollars, and logged to normalize the distributions). Firms established as subsidiaries or joint ventures may have access to financial resources of their parent firm(s), affecting their level of inventive activity and likelihood of patenting. To control for this possibility, we include a dummy variable coded one for firms with access to the resources of a corporate parent firm or firms, and zero otherwise.

Top management team size has also been associated with innovation and growth among high technology firms (Eisenhardt and Schoonhoven 1990). Therefore we control for the number of individuals occupying five key roles in each firm: President, General Manager, and Directors of R&D, Marketing, and Operations. When five different names were given for these positions, we coded top management team size equal to five; when four individuals were identified, size was coded four, and so on.

Although biotechnology is often used to describe an industry, it is more aptly characterized as a technology for manipulating microorganisms that, over time has manifested in specialized applications in different industrial sectors (agriculture, aquaculture, food and beverage, and human therapeutics, for example).[6] Patent application rates may also vary by technological focus. For example, commercialization is most challenging, and so patent protection most valuable, for developments in human therapeutics and vaccines where rigorous clinical trials and regulations

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[6] Technological focuses represented in our data include: 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, 16) contract research.

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).[7] In this regard, Prevezer (1995) finds that human medical applications of biotechnology exhibit the most pronounced tendency to cluster spatially. Therefore we control the effects of a firm's technological focus on its patent application rate with a set of fixed effects.

Lastly, we controlled for two variables capturing the effects of time. First, firm age, defined as the number of years since founding (logged to reduce skewness). Second, we controlled for year fixed effects. These variables help to ensure that any significant effects of the location variables are not a spurious result of age- or time-related learning or capability development processes.

Location Effects Specification. We measured the location of each firm based on its six-character postal code address. The form of the Canadian 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 region entirely within a province. The first three characters of the postal code identify the Forward Sortation Area (FSA). Each FSA is associated with a single postal facility from which mail delivery originates. The average FSA covers roughly 7,000 addresses. As of May 2001, there were about 1,600 FSAs in Canada (1,400 urban; 200 rural). For the analysis, we estimate location effects at three levels of aggregation corresponding to the first, first two, and first three postal code characters.[8] Figure 1 shows the locations of biotechnology firms in Canada for 1991 and 2000. Overall, the industry is highly and stably clustered within a relatively small number of compact, and primarily urban, areas.

Insert Figure 1 about here.

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[7] 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).

[8] The last three characters of the postal code identify the Local Delivery Unit (LDU). Each LDU represents one or more mail delivery points; the average number of unique addresses served by an LDU is approximately 15. As of May 2001, there were more than 750,000 Local Delivery Units.

Endogeneity Correction. Many factors influencing firms' inventiveness are themselves influenced by firms' inventiveness. For example, in addition to firms' investments in internal and collaborative R&D activities enhancing their subsequent inventiveness, inventive firms are more likely to make larger investments in internal and collaborative R&D activities. Similarly, while external financing enhances firms' inventiveness, inventive firms are also more likely to attract external financing. Because of this endogeneity, we implement Heckman's (1979) two-stage correction following the procedure outlined by Hamilton and Nickerson (2003). This correction involves first estimating the probability of a firm applying for a patent in a given year as a function of firm attributes as well as firm fixed effects, computing the Inverse Mills Ratio, and then estimating the patenting model as a function of firm attributes, location variables, and the Inverse Mills Ratio correction, the significance of which indicates the importance of the correction.[9, 10]

Identification of Inventive Locations

To identify inventive locations for biotechnology firms in Canada, we first estimated a baseline patent application rate model, which included firm-specific predictors of patenting, fixed effects for firms' technological focus and calendar year, as well as the Inverse Mills Ratio. We then proceeded to add location effects at smaller and smaller levels of aggregation, corresponding to the first, first two, and first three characters of the postal code.[11]

Model 1 in Table A2 in the Appendix shows the baseline firm-effects model, and Models 2 and 3 estimate location effects at the highest level of aggregation – the first postal code character.

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[9] The instrumental variable approach is also commonly used to correct for endogeneity, however, it is not appropriate for nonlinear estimators (Davidson and MacKinnon 1993).

[10] Adding a further correction for possible sample selection bias due to firm exit using a similar procedure did not alter the estimates.

[11] Descriptive statistics for firm and location variables are given in Table A1 in the Appendix. Correlations are generally low, with few exceeding .4 (16% shared variance), suggesting limited evidence of multicollinearity.

The likelihood ratio test given in the table indicates that location effects are important. In Model 2, the coefficient for the first postal code character 'E' (New Brunswick) is significantly lower than the omitted comparison group of locations with postal codes beginning with 'A' (Newfoundland); in all other locations, the coefficient is significantly higher. In Model 3, which adds New Brunswick to the omitted comparison group, all remaining locations are significant and positive. Thus, controlling for a detailed specification of firm effects, patent application rates are significantly higher for firms *not* located in Newfoundland and New Brunswick.[12]

We next examined location effects at the smaller two postal code character level of aggregation (see Tables A3 and A4 in the Appendix). To do this, in separate models, we disaggregated each positive first-character location into two or more fixed effects at the two-character level.[13] All other variables remain the same to maintain the correct specification for the fixed effects, which includes locations exhibiting positive coefficients, while excluding those with negative parameters as the 'uninventive' comparison group. As before, patent application rates are significantly higher for firms operating in two-character locations with positive coefficients relative to firms in locations with negative coefficients, as well as the omitted comparison group. For example, net of firm effects, firms located within postal codes beginning with K1, K2 and K7, applied for patents at a significantly higher rate than those located within postal codes beginning with K6 and K9. Thus, the more fine-grained two-character postal code distinctions matter, suggesting that the geographic scope of location effects operate at a scale smaller than a province or major region.

We next repeated the analysis at the still smaller, three-character aggregation corresponding to the FSA. To do this, in separate models, we disaggregated each positive two-character location in Tables A3 and A4 into two or more three-character or FSA fixed effects. All two-character locations

[12] In supplementary analysis, we confirmed that all 2- and 3-character postal code fixed effects for Newfoundland and New Brunswick were either insignificant, or significant and negative.

[13] Of course, only two-character postal codes where biotechnology firms operated appear in the analysis.

with negative coefficients in Tables A2 and A3 were dropped, adding them to the comparison group of uninventive locations.[14]

Estimates for FSA-level location effects are presented in Tables 1 and 2. In each model, a subset of the location effects is again significant and positive, indicating that the patent application rate is significantly higher for firms in these locations relative to the others within the same two-character location. Among firms within K1, K2, and K7, for example, those located within K1A, K1G, K1H, K1V, K2G, K2K, K7L and K7M applied for patents at a significantly higher rate than those located within K2E, K2L, and K2P, as well as all firms located in any FSA within K6 and K9 (omitted two-character locations with negative coefficients in Table A3). Thus, these more fine-grained FSA distinctions matter, indicating that the location effects operate at on relatively small, neighborhood scale.

Insert Tables 1-2 about here.

Finally, we estimated a combined model (not shown) that included a fixed effect for each of the 83 significant, positive FSAs in Tables 1 and 2, and excluded all negative or insignificant FSAs as the uninventive comparison group. Coefficients for all 83 FSA fixed effects remained significant and positive. With firm-specific predictors of the patent application rate controls, this means that biotechnology firms located within the FSAs with positive coefficients in Tables 1 and 2 applied for patents at a significantly higher rather than comparable firms located elsewhere.

Characteristics of Inventive Locations

Having distinguished inventive and uninventive locations, we now turn to an examination of the characteristics of the locations and the firms located within them. Given the likely dependence of a

[14] Again, of course, only FSAs where biotechnology firms operated appear in the analysis. In supplementary analysis, we again confirmed that all 3-character postal code fixed effects for the excluded 2-character locations were either insignificant, or significant and negative.

local environment's productivity on the scale of its resources, character of interactions among its firms, and its firms' internal and collaborative R&D activities, Table 3 compares inventive and uninventive FSAs and the firms comprising them on these key features.

Insert Table 3 about here.

Technological Scale and Focus. Research indicates that productive locations should exhibit technological scale and focus – that is, high concentrations of technologically-related resources. The logic of knowledge spillovers suggests that the value of external R&D resources likely depends on technological similarity and complementarity (Almeida and Rosenkopf 2003) and thus that the potential for benefiting from knowledge spillovers increases when firms with the same technological focus colocate. This occurs because the cumulativeness of advances and the properties of the knowledge base differ across technological focuses, rendering positive spillovers stronger within than across them. Thus, the concentration of biotechnology firms with a similar technological focus is more likely to create positive inventive productivity effects.

Comparison of means tests (Wonnacott and Wonnacott, 1970) given in Table 3 indicate that inventive FSAs contain greater scale concentrations of resources – human, technological, and financial. These resources are also more technologically focused, as indicated by the larger 'focus concentration' scores and numbers of 'same focus' firms.[15] Inventive FSAs are also more likely to include a university as well as a more other businesses. Thus, while operating in locations with a high concentration of technically similar firms increases potential spillovers, so too does operating in locations with potential spillovers from public and diverse private sector inventive activity (Anselin, Varga and Acs 1997; Jacobs 1969; Feldman and Audretsch 1999).

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[15] Focus concentration scores for each FSA were computed as a Herfindahl Index – the sum of the squared proportions of firms focused on each of the 16 technological areas noted earlier. Scores were normalized, ranging from 0 (dispersed across focuses) to 1 (single focus).

Norms of Cooperation and R&D Investment. Social accounts of interfirm cooperation point to cohesion as a central factor facilitating such trust and openness among firms (Calabrese, Baum and Silverman, 2000; Uzzi 1996). Under the influence of norms of cooperation, the operation of social and professional networks, widely held to serve as vital channels for the exchange and diffusion of information and ideas (Jaffe, et al. 1993), is enhanced. The presence of universities and in particular university spinoffs may reinforce the emergence of this collaborative orientation. Spinoffs diffuse university norms of open science and collaboration, fostering a local culture of learning and cooperation, encouraging other firms to establish links with local universities and each other, as well as reinforcing the operation of social and professional networks that serve as channels for the exchange, diffusion and integration of information and ideas (Owen-Smith & Powell, 2004). Local industrial organization and culture thus mediate the effects of local technological capabilities (Saxenian 1994).

Consistent with this account, inventive FSAs are characterized by a greater emphasis on collaboration. As Table 3 shows, inventive FSAs exhibit more extensive cooperation between resident firms and universities, other upstream research partners, as well as R&D alliances with other biotechnology firms and downstream alliances with complementary partners.

Norms of R&D investment are also evident in inventive FSAs. In addition to their propensity to engage in collaborative R&D, firms in inventive FSAs employ two to three times the number of R&D employees as firms in uninventive FSAs. While such investments in part reflect the different operational scale of firms located in inventive and uninventive FSAs, it may also reflect a virtuous dynamic of research activity within a given location. If firms in a location invest in a high level of R&D activity, the local pool of new knowledge into which they can tap into will be rich. And, since research performs the dual role of both generating new knowledge as well as absorbing new knowledge generated by other firms (Cohen and Levinthal 1990), firms will find it attractive to invest in R&D as well. Of course, low-level R&D equilibria in which the level of new knowledge is too limited to motivate firms to invest are also possible. Thus, at the local level, there are increasing returns to R&D investment, and locations settling at high-level equilibria will tend to outperform those settling at low-level equilibria.

Innovation and Survival. As Table 3 shows, firms in inventive FSAs apply for a significantly larger number of patents than those located in uninventive FSAs. As noted earlier, however, a high rate of inventive output may not correspond to innovative output or commercial significance. Therefore, to assess the innovative and commercial value of firms' inventive output more directly, we collected patent citation data and computed 'forward citations' for each patent (Trajtenberg 1990; McGahan and Silverman 2006). Forward citations were measured as the number of times a patent was cited by other patents in the first five years after its granting, with more highly-cited patents being more innovative and valuable. Aggregating forward citations for patents granted to firms located inventive and uninventive FSAs, we found that firms located in inventive FSAs received an average of 2.86 (S.D. = 5.58) forward citations per patent, while those located in uninventive FSAs received an average of .71 (S.D. = 1.12) forward citations. The socioeconomic value of patenting in inventive FSAs thus appears to be much greater.

Firms in inventive FSAs exhibit higher revenues than those in uninventive FSAs, but this difference is not significant (see Table 3). Revenues, however, are a problematic performance indicator in biotechnology since prior to commercialization even the most inventive firms earn little revenue. A performance measure more relevant to small, technology-based firms is survival (Rothaermel and Thursby 2005). Underscoring the significance of survival in our empirical setting, recall that 264 of the 675 firms (39.1%) in our sample ceased operations during the 1990s. Notably, however, the exit rate was 24.9% (62 of 249 firms) in inventive FSAs, and 47.4% (202 of 426 firms) in uninventive FSA. Thus, reinforcing the distinction between inventive and uninventive locations, despite their younger age, the exit rate in inventive FSAs was half that of uninventive FSAs.

Inventive and Uninventive Firm Characteristics. Table 3 also shows that the average firm located within an inventive FSA is endowed with significantly greater internal and external resources than the average firm located within an uninventive FSA, again despite their younger age. There is, however, significant variation among firms within inventive FSAs, suggesting that, within inventive FSAs, there may be uninventive firms that resemble firms located in uninventive FSAs. To examine this possibility, in Table 4, we contrast inventive and uninventive firms within inventive FSAs, the latter of which applied for no patents during the 1990s.

Insert Table 4 about here.

Within inventive FSAs, uninventive firms appear to be at a decided disadvantage to their inventive counterparts. Comparison of means tests in Table 4 indicate that, in addition to having applied for more patents in the past, inventive firms are better financed, more likely to be university spinoffs (less likely to have a corporate parent), invest more in R&D, have larger top management teams, and more upstream, downstream and biotech alliances than their uninventive counterparts. Nevertheless, as the final column of the table indicates, uninventive firms located within inventive FSAs do tend to have greater access to alliances and human and financial capital than uninventive firms in uninventive FSAs (see Table 3). A notable distinguishing feature of uninventive firms located in inventive FSAs is their greater likelihood of being a corporate subsidiary.

Location of Inventive FSAs

Figures 2, 3 and 4 show the boundaries of FSAs for Canada's three largest urban centers, Montreal, Toronto and Vancouver, respectively. In the figures, inventive FSAs are shaded darkly, uninventive FSAs shaded lightly, and FSAs without biotechnology firms unshaded.

Insert Figures 2, 3 and 4, and Table 5 about here.

Inventive FSAs tend to be clustered together, while uninventive FSAs tend either to surround these clusters, or be located away from them. Evidence of this pattern is summarized in Table 5, which gives the percentage of FSAs that are adjacent to zero, one, two or three other inventive FSAs. Relative to inventive FSAs, uninventive FSAs are more than twice as likely to neighbor no inventive FSAs (44% vs. 20%), equally likely to neighbor one inventive FSA (34% vs. 37%), and half as likely to neighbor two or three inventive FSAs (22% vs. 43%). The location pattern of inventive and uninventive FSAs thus suggests that productive locations may often be comprised of clusters of FSAs, rather than individual FSAs.

Variation in Inventive FSAs. To this point, we have implicitly assumed that all inventive FSAs are alike. However, the variation revealed in Tables 3 and 4 suggests that inventive FSAs may differ substantially. To examine the extent to which this variation reflects systematic differences, we compare the characteristics of inventive FSAs and the firms located within them across Canada's three largest urban centers in Table 6.

Insert Table 6 about here.

Within locations, the patterns of differences between inventive and uninventive FSAs largely replicate the overall differences in Table 3.[16] More pronounced within these metropolitan areas, however, is that collaborative resources (e.g., alliances, corporate parents, spinoff status) and technical focus (e.g., focus concentration, number of same focus firms) more clearly distinguish inventive from uninventive FSAs. Scale also plays a role, but not with respect to technical resources (e.g., R&D employees and spending) on which uninventive FSAs are typically comparable. The nature of these distinctions point to the significance of industrial organization in general and collaborative activities in particular, in fostering inventive activity within a location.

[16] For simplicity, values for uninventive FSAs are not presented.

The differences across locations are striking. Vancouver's inventive FSAs are comprised of younger firms, a larger proportion of university spinoffs, more likely to contain a university, and characterized by more extensive cooperation with universities and other upstream research partners. Individually, the firms located within Vancouver's FSAs also exhibit these differences.

Toronto's inventive FSAs contain larger concentrations of older firms, patent applications and R&D spending, exhibit a higher proportion of corporate subsidiaries, are more technologically focused, and characterized by more extensive cooperation between local firms and other biotechnology firms and downstream commercialization partners. Toronto's inventive FSAs are also more likely to include a larger number of other businesses. Notably, the resource advantages of Toronto's inventive FSAs stem largely from their scale; individually, the firms located within Toronto's FSAs do not exhibit these differences.

Montreal's inventive FSAs, in contrast, exhibit few distinguishing features, although firms located within them have a higher likelihood of being corporate subsidiaries, and are comprised of more limited resources – human, technological, and financial.

Thus, Vancouver's inventive FSAs appear to derive an advantage from superior access to university and other research-related resources, while Toronto's inventive FSAs derive an advantage from their resource scale and technical focus. Montreal's inventive FSAs do not appear to have a 'distinctive' advantage, although they do have greater access to collaborative resources than Montreal's uninventive FSAs, and achieve parity with FSAs in Vancouver and Toronto across a range of location and firm features.

As a final step in the analysis, in Table 7, we distinguish between inventive and uninventive firms (i.e., applied for no patents during the 1990s) in these inventive FSAs. In addition to applying for a significantly larger number of patents in the past, compared to their uninventive counterparts, inventive firms in all three metropolitan areas are significantly more likely to be university spinoffs, have larger management teams, and engage in more upstream R&D alliances. Inventive firms in Vancouver and Toronto's (but not Montreal's) inventive FSAs also engage in more university alliances. The patterns of differences across locations are also quite similar for inventive and uninventive firms, particularly for Vancouver and Montreal, as well as to the configuration in Table 6. Table 7 thus offers no further insight into the advantage behind Montreal's inventive FSAs. Taken together, the comparisons in Table 7 suggest that uninventive firms in inventive FSAs tend to be 'disadvantaged' versions of their inventive counterparts.

Insert Table 7 about here.

Discussion and Conclusion

We were motivated in this study by our limited understanding of factors influencing the relative productivity of different locations, and in particular how firms' investments in internal and collaborative capabilities influence the degree to which they benefit from clustering. To address this question, using detailed firm-level data on Canadian biotechnology firms during the 1990s, we examined the identity and geographic scale of inventive and uninventive locations, the characteristics of inventive and uninventive locations and the firms comprising them, as well as the location of inventive locations and variation in their characteristics.

Although locations differed significantly in their effect on firms' inventive output at high levels of aggregation (i.e., province), consistent with other recent research location effects (e.g., Aharonson et al. 2007; Globerman et al. 2005; Rosenthal and Strange 2003; Stuart and Sorenson 2003; Wallsten 2001), we also distinguished inventive and uninventive locations at much lower levels of aggregation. The smallest we considered was the Forward Sortation Area (FSA), which corresponds to the first three characters of Canadian postal codes, and covers roughly 7,000 postal addresses. Our results indicate that agglomeration effects do not take place at provincial, regional or even metropolitan levels, but rather at the level of local neighborhoods. As Figures 2, 3 and 4 show, Montreal, Toronto and Vancouver are comprised of a mix of inventive and uninventive FSAs, with inventive FSAs themselves tending to cluster together, and uninventive FSAs tending to be more isolated. Thus, our findings indicate that empirical effects of regional agglomerations may mask significant variation in inventiveness that depends on localized characteristics of neighboring firms. The clustering of inventive FSAs indicates that location effects may operate across areas somewhat larger than single FSAs, pointing to the need for future work that is more flexible in its specification of the scale of location effects and sensitive to the likelihood that these occur within small geographic areas.

Also consistent with past studies, inventive FSAs exhibited significantly greater resource scale and technological focus, as well as a greater emphasis on R&D investment and public and private collaboration. Inventive FSAs contain more R&D employees, more R&D spending and grants, and are thus likely sources of substantial knowledge spillovers. They also contain more interfirm alliances, universities, and university spinoffs and collaborations, indicative of the existence of professional and social networks vital to knowledge diffusion within local neighborhoods. Notably, while inventive FSAs tend to contain a greater proportion of firms sharing a technological focus, they also exhibit a high concentration of other types of business activity, suggesting the operation of urbanization economies as well (Jacobs 1969).

The ability of firms to benefit from a location is not uniform. Despite the advantages of inventive FSAs, some firms located within them were unable to profit. These 'uninventive' firms operating within inventive FSAs possess more limited internal and external resources than their inventive counterparts. Inventive firms are better financed, more likely to be a university spinoff, less likely to have a corporate parent, invest more in R&D, have larger top management teams, and more upstream, downstream and biotech alliances than their uninventive counterparts. Notably, it is not internal R&D resources, but collaborations and university ties via spinoffs that are the strongest factors discriminating between inventive and uninventive firms in inventive FSAs. For a given inventive location, what makes the difference between inventive and uninventive firms is not the level of R&D effort; it is access to the network of interfirm and university collaboration.

Thus, it is not enough to collocate with and match the R&D effort of inventive firms; to capture the benefits of external sources of knowledge fully a firm must participate in the collaboration network. Future work might therefore usefully examine differences in the ways firms capture (or do not) externalities given their R&D intensity and integration within collaborative networks. Of particular interest is the degree to which inventive and uninventive locations are comprised of firms that are more or less local in their collaborations, and thus more or less constrained in their access to diverse information, resources, and locations (Owen-Smith and Powell 2004).

Our more fine-grained comparison of inventive locations within three major metropolitan areas – Vancouver, Toronto and Montreal – revealed that inventive locations vary in their emphasis on scale and technological focus relative to collaboration, suggesting that location advantages can develop in multiple ways, even within the same industry. And in particular, suggest different combinations of advantages, where the absence of one (e.g., scale or focus) may be compensated for by an abundance of another (e.g., interfirm alliances, universities). Thus, while Vancouver's inventive FSAs exhibited significantly lower R&D expenditures than Toronto's inventive FSAs, they appear to compensate with significantly greater university affiliations. This equifinality indicates the need for future work comparing and contrasting the ways in which locations produce benefits and how firms might best take advantage of them would be fruitful.

Many jurisdictions are investing resources to promote the formation of productive biotechnology and other high-technology clusters. The insights our findings offer into factors associated with inventive locations may facilitate such efforts. Concentrating resources around a single technological focus is likely to prove more valuable than dispersing resources among a variety of technologies. But, while local technological focus and scale are necessary, they do not appear sufficient to produce a location advantage. Harvesting location benefits depend importantly on industrial organization (e.g., the degree of collaboration and knowledge sharing among local firms), R&D investments in invention and absorptive and collaborative capacities, as well as access to universities and urbanization economies.

National and regional policies aimed at fostering the creation and expansion of specialized clusters thus seem warranted, particularly in urban areas, and if coupled with support for development of collaborative research initiatives and capabilities involving firms and neighboring universities. One such example is the MaRS (Medical and Related Sciences) Center, located in Toronto's 'Discovery District', a two square kilometer area designated as the city's innovation center. MaRS houses research labs and firms, as well as business advisors, investors, and professional services. It is colocated with the University of Toronto, its teaching hospitals, and research institutes, and is adjacent to city's financial district, and provincial government offices. Policies aimed at fostering the diversification of existing clusters or investing resources to promote cluster formation in more remote jurisdictions (particularly those without a significant university presence) are likely to be ill-advised, and to result in a suboptimal geographic organization of the industry.

Our findings also indicate that there is no one best way to promote location advantages, highlighting the importance of local characteristics, particularly industrial organization, to identifying effective supportive activities. In our study, the maturity of an inventive location, indexed by the average age of its firms, appears to be an important indicator of effective policy initiatives. In

Vancouver's inventive FSAs, tend to be younger, are often university spinoffs, and their ties with universities influential in their inventiveness. In Toronto's inventive FSAs, firms tend to be older, and to establish more downstream alliances to access production and commercialization facilities. The firms are also more often subsidiaries, a common fate for more advanced firms with promising inventions requiring substantial resources to support their commercialization. In Montreal's inventive FSAs, firms tend to be middle-aged vis-à-vis their Vancouver and Toronto counterparts, but on par with them across a range of location and firm features. Although we doubt the generalizability of this particular configuration of advantages (collaboration vs. scale and focus), we expect that other technology sectors in Canada and elsewhere exhibit analogous regional differences, and that inventiveness is strongly an attribute of regions. We suspect that the particular pattern of advantages observed will depend on technology-specific factors.

These differences in maturity point to distinct support activities. In younger inventive locations, where advantages reside in the quality of the interplay and ties among local actors, an emphasis on supporting networking among firms and with local universities, as well as investment in university research and collaboration capabilities is required. So too is attention to the spatial organization of firms; new firms should be encouraged to locate within inventive areas, and firms located in uninventive areas to relocate to them. In older inventive locations, where advantages are driven more by technological scale and access to financial and downstream collaborative resources, an emphasis on building a local reputation for commercial viability is necessary to attract financers and corporate partners to support firms' commercial development. In 'adolescent' inventive locations transitioning from youth to maturity, a focus on facilitating the shift in local advantage based on the quality of collaborative resources to one based on technological scale is required. An emphasis on building a local reputation for invention is also necessary to attract financers and corporate partners to support firms' further research development. These observations highlight the dynamism of location advantages, and the need for policy makers to anticipate the need for supportive actions to facilitate such transitions, and potentially, renewal.

Evidence is mounting that geographic concentration contributes to firms' inventiveness, but we lack understanding of factors influencing the relative productivity of locations beyond variation in their scale and technological focus. We find that, while the productivity of a local environment indeed depends on the scale and focus of available inputs, it also depends on the way in which these inputs are organized and interact. For a given technology and place, local industrial organization influences the quality and intensity of location benefits. The ability of particular firms to benefit from a location is, in turn, a function of their capacity to absorb local knowledge spillovers. A 'hybrid' approach to clustering, linking location, capabilities and networks, thus promises to advance our understanding of a range of phenomena central to the inventive capacity of firms and economies.

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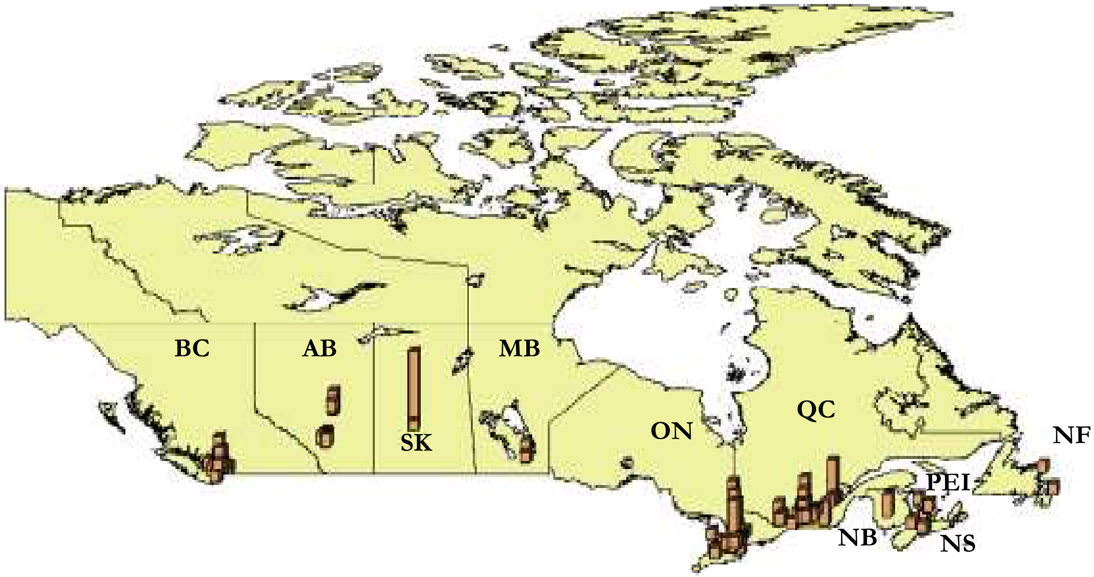
Figure 1. Geographic Location of Biotechnology Firms in Canada

1991



2000

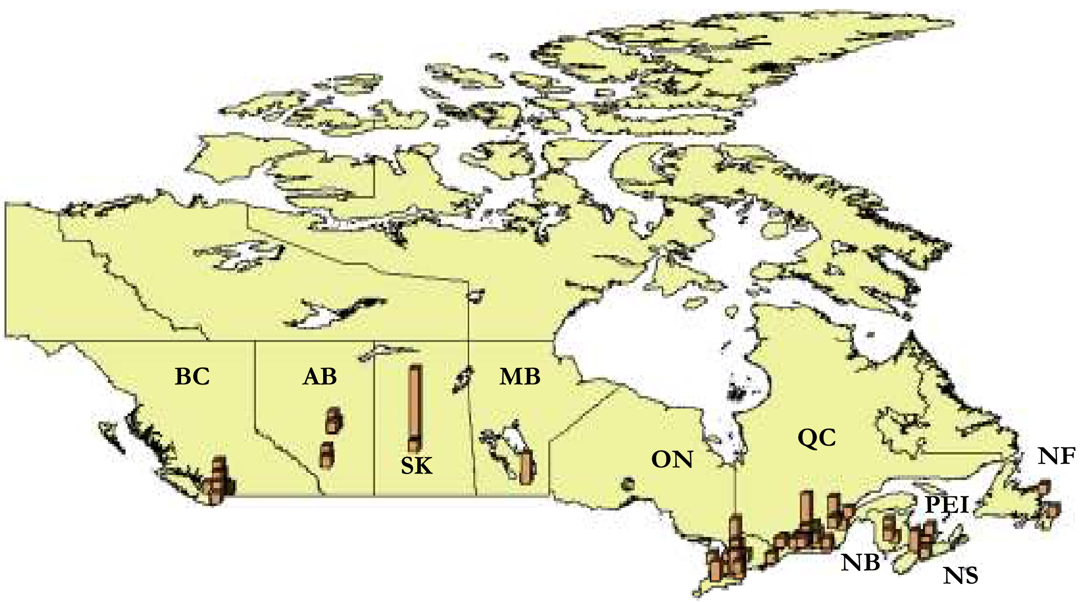


Figure 2. Inventive Productivity of Montreal FSAs

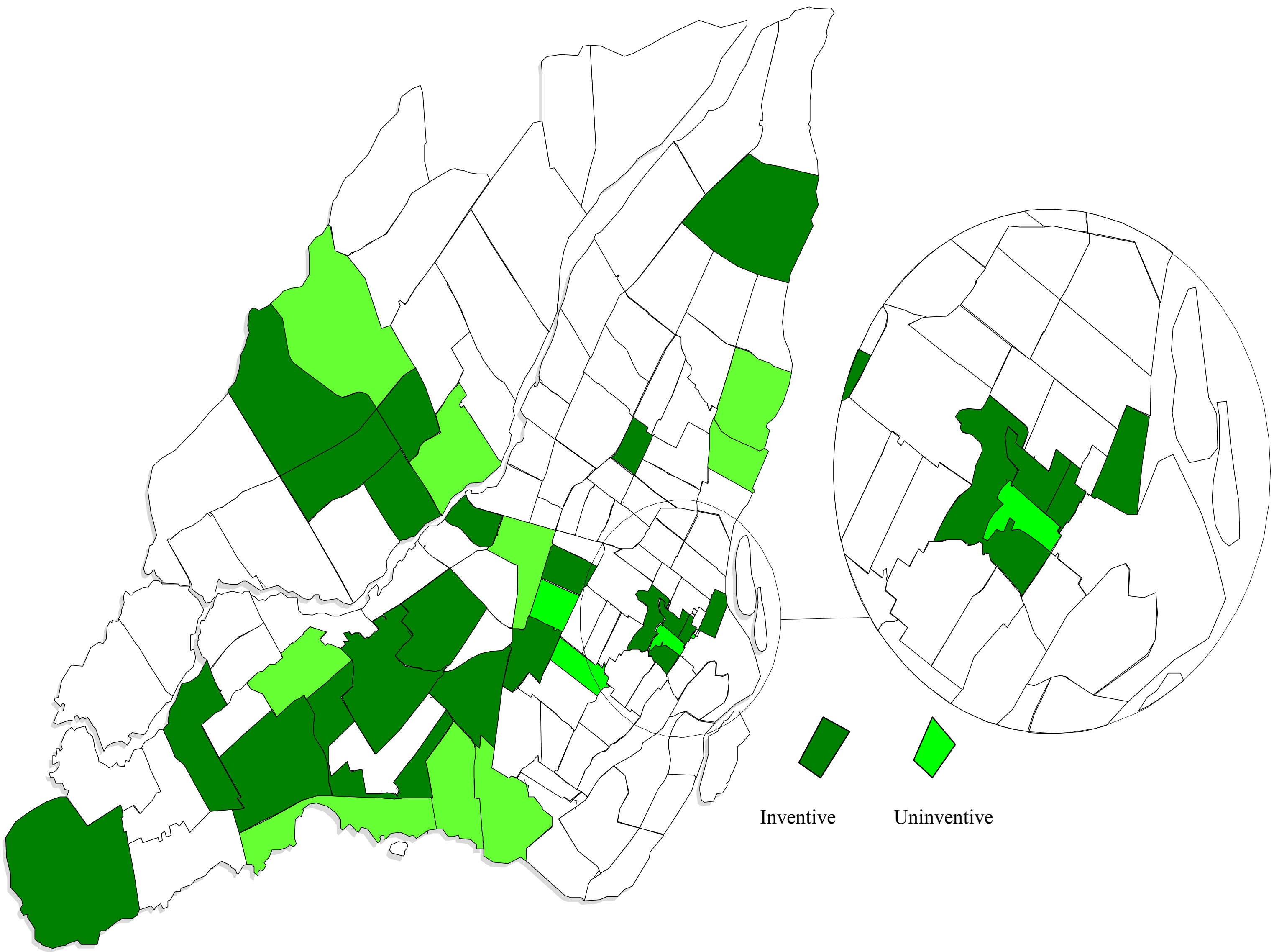


Figure 3. Inventive Productivity of Greater Toronto FSAs

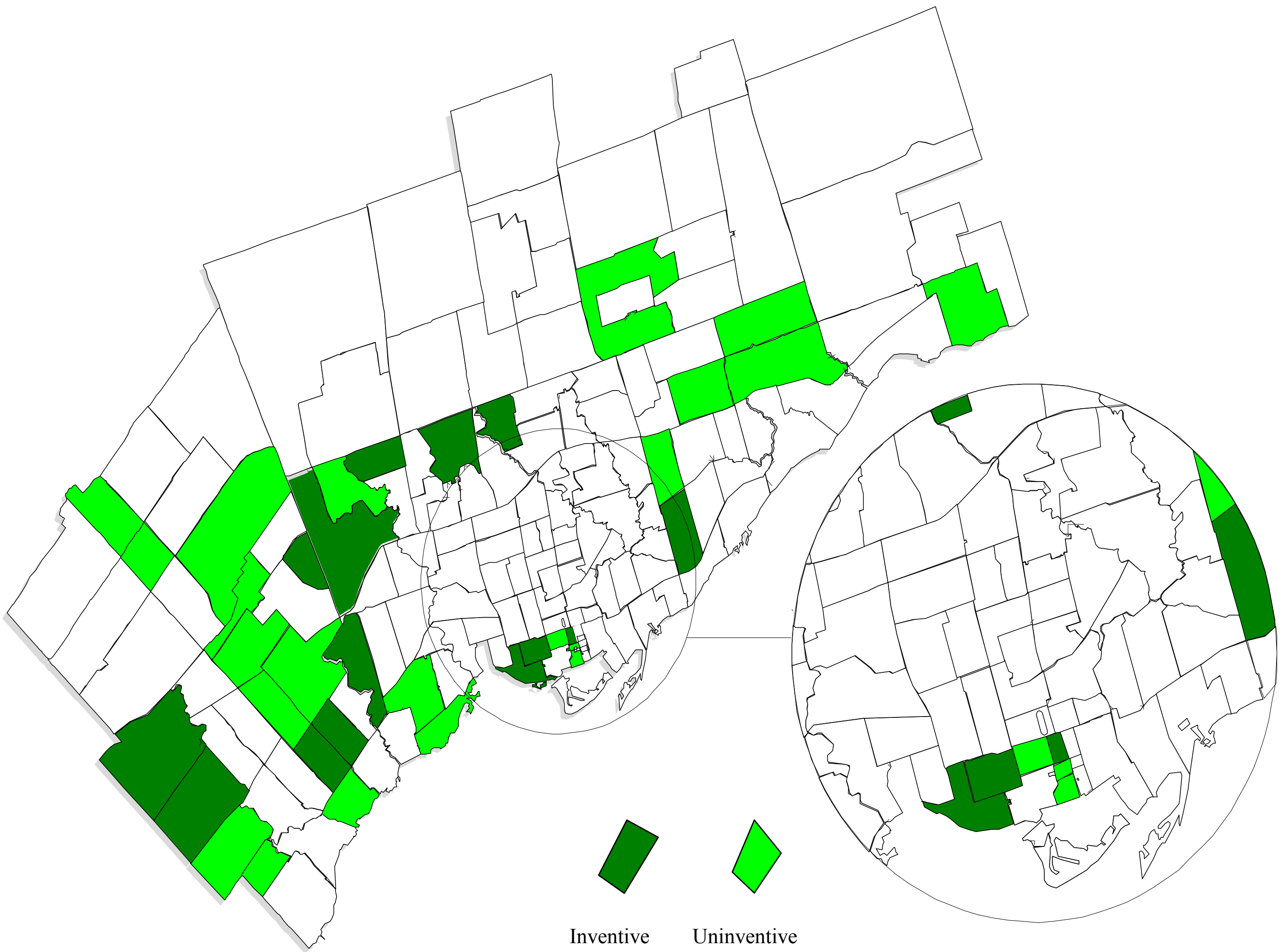


Figure 4. Inventive Productivity of Vancouver FSAs

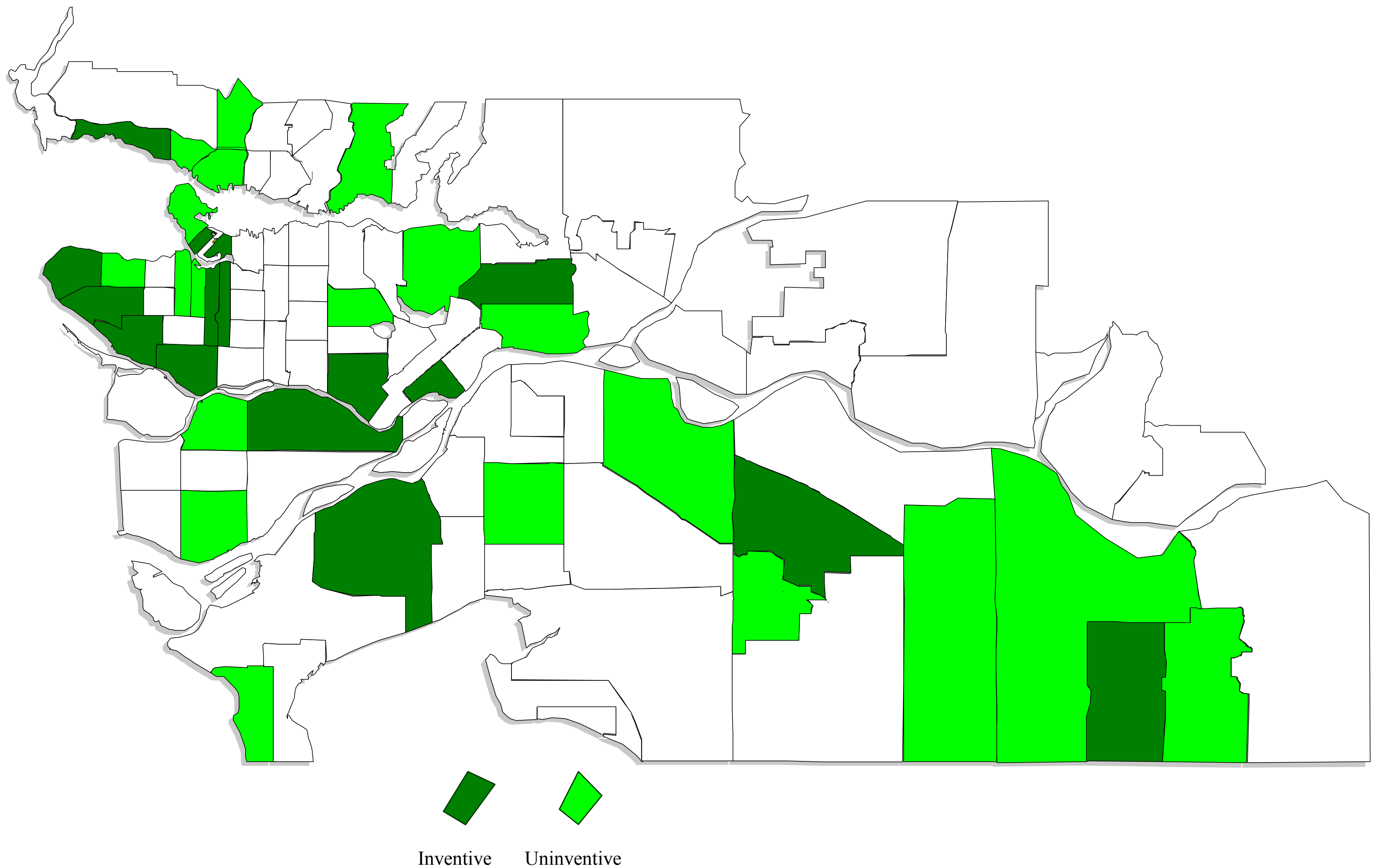


Table 1. Robust Negative Binomial Models of Patent Application Rates: First Three Postal Code Characters (FSA)

		B (Nova Scotia)			C (Prince Edward Island)			G (Quebec - East)			H (Montreal)			J (Quebec - West)			K (Ontario - Southeast)			L (Ontario - South Central)	
Variable		Coef.	S.E.		Coef.	S.E.		Coef.	S.E.		Coef.	S.E.		Coef.	S.E.		Coef.	S.E.		Coef.	S.E.
Patent 5 Years		.023	(.006) ***		.023	(.006) ***		.024	(.006) ***		.021	(.006) ***		.023	(.006) ***		.020	(.007) **		.021	(.006) ***
Ln(Age)		-.115	(.082) +		-.103	(.083)		-.112	(.084) +		-.103	(.083)		-.103	(.083)		-.099	(.093)		.085	(.088)
Ln(R&D Expenditures)		.010	(.011)		.010	(.011)		.008	(.011)		.008	(.011)		.010	(.011)		.004	(.011)		.005	(.012)
Ln(R&D Employees)		.050	(.055)		.048	(.056)		.042	(.057)		.092	(.064) +		.048	(.056)		.055	(.065)		.015	(.054)
ln(Revenue)		.005	(.009)		.004	(.009)		.005	(.010)		.007	(.011)		.004	(.009)		.010	(.010)		.004	(.010)
Ln(Totfin)		.015	(.009) +		.015	(.009) +		.014	(.009) +		.012	(.011)		.015	(.009) +		.015	(.009) +		.015	(.010) +
Ln(IRAP)		-.006	(.017)		-.008	(.017)		-.008	(.017)		-.005	(.018)		-.008	(.017)		-.007	(.017)		-.003	(.016)
Spin-Off		.185	(.179)		.199	(.179)		.194	(.179)		.028	(.192)		.199	(.179)		.289	(.188) +		.273	(.191) +
Parent		.282	(.160) *		.257	(.163) +		.251	(.164) +		.304	(.168) *		.257	(.163) +		.351	(.171) *		-.165	(.148)
TMT Size		.049	(.057)		.056	(.058)		.056	(.060)		.107	(.065) *		.056	(.058)		.060	(.061)		.011	(.054)
University Alliance		-.006	(.090)		-.006	(.089)		-.010	(.089)		.053	(.094)		-.006	(.089)		.016	(.088)		.035	(.090)
Upstream Alliance		-.109	(.055) *		-.116	(.057) *		-.116	(.057) *		-.090	(.069)		-.116	(.057) *		-.091	(.058) +		-.133	(.057) **
Downstream Alliance		-.047	(.030) +		-.048	(.031) +		-.047	(.031) +		-.061	(.036) *		-.048	(.031) +		-.041	(.030) +		-.040	(.031) +
Biotechnology Alliance		-.125	(.051) **		-.130	(.051) **		-.132	(.051) **		-.149	(.058) **		-.130	(.051) **		-.112	(.048) **		-.130	(.050) **
Positive 2-Character Postal Codes																					
B (Nova Scotia)					11.784	(.654) ***		11.488	(.652) ***		11.190	(.662) ***		11.831	(.653) ***		14.019	(.574) ***		12.611	(.628) ***
C (Prince Edward Island)		12.198	(.640) ***					11.198	(.618) ***		10.808	(.675) ***		11.549	(.622) ***		13.473	(.572) ***		12.223	(.579) ***
G (Quebec - East)		12.203	(.674) ***		11.537	(.680) ***					10.896	(.712) ***		11.584	(.678) ***		13.427	(.638) ***		12.527	(.643) ***
H (Montreal)		12.544	(.642) ***		11.874	(.643) ***		11.567	(.642) ***					11.921	(.642) ***		13.783	(.614) ***		12.910	(.596) ***
J (Quebec - West)		11.672	(.664) ***		10.998	(.658) ***		10.672	(.664) ***		10.439	(.698) ***					12.991	(.638) ***		12.063	(.619) ***
K (Ontario - Southeast)		12.641	(.653) ***		11.956	(.643) ***		11.684	(.638) ***		11.222	(.678) ***		12.003	(.644) ***					12.863	(.608) ***
L (Ontario - South Central)		13.218	(.668) ***		12.539	(.661) ***		12.228	(.663) ***		11.914	(.702) ***		12.586	(.662) ***		14.445	(.595) ***			
M (Toronto)		12.583	(.631) ***		11.888	(.616) ***		11.588	(.613) ***		11.311	(.661) ***		11.936	(.616) ***		13.863	(.502) ***		12.747	(.581) ***
N (Ontario - Southwest)		11.537	(.682) ***		10.877	(.686) ***		10.574	(.681) ***		10.104	(.737) ***		10.925	(.684) ***		12.751	(.713) ***		12.268	(.618) ***
R (Manitoba)		12.021	(.678) ***		11.353	(.678) ***		11.037	(.679) ***		10.653	(.712) ***		11.400	(.676) ***		13.228	(.619) ***		12.448	(.641) ***
S (Saskatchewan)		12.664	(.646) ***		12.003	(.651) ***		11.703	(.649) ***		11.321	(.690) ***		12.050	(.650) ***		13.971	(.612) ***		12.867	(.615) ***
T (Alberta)		12.083	(.652) ***		11.387	(.637) ***		11.081	(.635) ***		10.851	(.673) ***		11.435	(.636) ***		13.340	(.573) ***		12.451	(.606) ***
V (British Columbia)		12.271	(.648) ***		11.599	(.644) ***		11.301	(.642) ***		10.957	(.685) ***		11.646	(.643) ***		13.506	(.561) ***		12.552	(.610) ***
3-Character Postal Code (FSA)																					
	B3B	-.712	(1.005)	C1A	-3.798	(1.362) **	G1G	-1.085	(1.290)	H1B	11.592	(.724) ***	J7E	11.051	(.661) ***	K1A	15.029	(.636) ***	L3R	12.257	(.709) ***
	B3H	1.244	(.983)	C1E	11.502	(.621) ***	G1K	11.401	(.818) ***	H1W	-.640	(1.370)	J7J	2.712	(1.367) *	K1G	13.325	(.653) ***	L4B	-2.057	(1.058) *
	B3J	.656	(1.185)				G1N	10.922	(.646) ***	H2A	11.508	(.747) ***	J7R	-.834	(1.292)	K1H	13.130	(.599) ***	L4G	-.862	(1.077)
	B3K	-8.476	(.803) ***				G1P	11.744	(.623) ***	H2H	-.850	(1.433)	J7V	-5.883	(1.250) ***	K1V	15.519	(.581) ***	L4V	13.385	(.638) ***
	B3L	12.762	(.749) ***				G1S	-.697	(1.337)	H2L	-.917	(1.440)				K2E	-1.047	(1.229)	L4W	-4.684	(1.152) ***
	B3T	-2.706	(1.318) *				G1V	11.031	(.628) ***	H2M	-1.223	(1.459)				K2G	14.099	(.627) ***	L4Y	12.164	(.638) ***
							G1W	.094	(1.338)	H2P	-.899	(1.198)				K2K	13.511	(.642) ***	L4Z	-2.435	(1.205) *
										H2X	-.916	(1.397)				K2L	-1.707	(1.320)	L5A	11.029	(.873) ***
										H2Y	11.391	(.598) ***				K2P	1.587	(1.163)	L5G	-1.081	(1.252)
										H2Z	-.581	(1.134)				K7L	13.074	(.852) ***	L5K	-.478	(1.304)
										H3A	10.403	(.738) ***				K7M	13.124	(.661) ***	L5L	-1.621	(1.262)
										H3B	11.722	(.710) ***							L5M	12.427	(.642) ***
										H3C	-1.032	(1.434)							L5N	14.383	(.634) ***
										H3G	-6.065	(1.257) ***							L5S	.044	(1.305)
										H3H	11.356	(.697) ***							L5T	-1.049	(.914)
										H3J	-.198	(1.436)							L7L	-.840	(1.006)
										H3M	10.432	(.776) ***							L7N	9.994	(.870) ***
										H3P	10.263	(.718) ***							L7P	-.682	(1.284)
										H3R	-1.026	(1.449)							L7T	-.792	(1.255)
										H3W	-1.006	(1.428)									
										H4N	-.634	(1.394)									
										H4P	10.444	(.778) ***									
										H4R	11.531	(.730) ***									
										H4S	11.630	(1.111) ***									
										H4T	11.270	(.676) ***									
										H7N	-1.036	(1.349)									
										H7P	16.947	(1.024) ***									
										H7S	11.899	(.715) ***									
										H7T	11.653	(.722) ***									
										H7V	11.221	(.757) ***									
										H9H	11.420	(.748) ***									
										H9P	12.346	(.784) ***									
										H9R	10.532	(.727) ***									
										H9S	-1.151	(1.450)									
										H9X	11.836	(.795) ***									
Technology Fixed Effects		Incl.			Incl.			Incl.			Incl.			Incl.			Incl.			Incl.	
Year Fixed Effects		Incl.			Incl.			Incl.			Incl.			Incl.			Incl.			Incl.	
Inverse Mills Ratio		-1.842	(.112) ***		-1.845	(.112) ***		-1.836	(.113) ***		-1.856	(.127) ***		-1.844	(.112) ***		-1.872	(.116) ***		-1.767	(.106) ***
Constant		-10.854	(.727) ***		-10.226	(.754) ***		-9.912	(.757) ***		-9.794	(.809) ***		-10.273	(.754) ***		-12.327	(.777) ***		-11.384	(.717) ***
Log-Likelihood		-664.21			-665.40			-664.97			-657.73			-665.39			-657.30			-655.68	
Likelihood Ratio Test (df)		38.3			35.9			36.8			51.3			36.0			52.2			55.4	

Note: + p<.10, * p<.05, ** p<.01, *** p<.001. The Sample included 2211 annual observations.

Table 2. Robust Negative Binomial Models of Patent Application Rates: First Three Postal Code Characters (FSA)

		M (Toronto)			N (Ontario - Southwest)			R (Manitoba)			S (Saskatchewan)			T (Alberta)			V (British Columbia)	
Variable		Coef.	S.E.		Coef.	S.E.		Coef.	S.E.		Coef.	S.E.		Coef.	S.E.		Coef.	S.E.
Patent 5 Years		.022	(.006) ***		.023	(.006) ***		.023	(.006) ***		.023	(.006) ***		.020	(.007) **		.024	(.007) ***
Ln(Age)		-.088	(.086)		-.102	(.083)		-.103	(.083)		-.102	(.082)		-.105	(.085)		-.073	(.099)
Ln(R&D Expenditures)		.008	(.013)		.010	(.011)		.010	(.011)		.010	(.011)		.010	(.011)		.015	(.011) +
Ln(R&D Employees)		.068	(.061)		.050	(.056)		.048	(.056)		.046	(.056)		.034	(.058)		.042	(.059)
ln(Revenue)		.003	(.010)		.004	(.009)		.004	(.009)		.003	(.010)		.004	(.009)		.003	(.010)
Ln(Totfin)		.016	(.009) *		.014	(.009) +		.015	(.009) +		.015	(.009) +		.015	(.009) *		.012	(.010)
Ln(IRAP)		-.012	(.017)		-.007	(.017)		-.008	(.017)		-.008	(.017)		-.004	(.017)		-.004	(.019)
Spin-Off		.271	(.190) +		.201	(.180)		.199	(.179)		.204	(.179)		.062	(.215)		.329	(.203) +
Parent		.252	(.179) +		.265	(.163) *		.257	(.163) +		.276	(.165) *		.257	(.176) +		.251	(.167) +
TMT Size		.057	(.059)		.059	(.059)		.056	(.058)		.061	(.058)		.056	(.059)		.092	(.064) +
University Alliance		.024	(.089)		-.005	(.089)		-.006	(.089)		-.010	(.090)		.014	(.095)		-.013	(.098)
Upstream Alliance		-.138	(.057) **		-.120	(.058) *		-.116	(.057) *		-.108	(.056) *		-.113	(.060) *		-.123	(.064) *
Downstream Alliance		-.042	(.034)		-.047	(.031) +		-.048	(.031) +		-.042	(.031) +		-.039	(.028) +		-.056	(.032) *
Biotechnology Alliance		-.154	(.055) **		-.127	(.051) **		-.130	(.051) **		-.135	(.050) **		-.125	(.048) **		-.134	(.054) **
Positive 2-Character Postal Codes																		
B (Nova Scotia)		11.517	(.646) ***		11.495	(.654) ***		11.513	(.652) ***		11.425	(.653) ***		13.190	(.691) ***		12.010	(.659) ***
C (Prince Edward Island)		11.114	(.625) ***		11.228	(.623) ***		11.231	(.620) ***		11.137	(.621) ***		12.724	(.651) ***		11.750	(.629) ***
G (Quebec - East)		11.246	(.674) ***		11.262	(.680) ***		11.266	(.677) ***		11.186	(.675) ***		12.824	(.698) ***		11.775	(.685) ***
H (Montreal)		11.559	(.647) ***		11.595	(.643) ***		11.603	(.640) ***		11.499	(.641) ***		13.125	(.675) ***		12.075	(.655) ***
J (Quebec - West)		10.751	(.660) ***		10.721	(.661) ***		10.727	(.657) ***		10.652	(.657) ***		12.302	(.679) ***		11.181	(.670) ***
K (Ontario - Southeast)		11.603	(.649) ***		11.675	(.645) ***		11.685	(.641) ***		11.591	(.641) ***		13.256	(.656) ***		12.154	(.648) ***
L (Ontario - South Central)		12.272	(.661) ***		12.249	(.664) ***		12.268	(.660) ***		12.173	(.660) ***		13.831	(.687) ***		12.665	(.670) ***
M (Toronto)					11.601	(.619) ***		11.617	(.615) ***		11.530	(.615) ***		13.159	(.656) ***		12.023	(.633) ***
N (Ontario - Southwest)		10.601	(.681) ***					10.606	(.683) ***		10.490	(.688) ***		12.133	(.721) ***		11.016	(.714) ***
R (Manitoba)		11.058	(.675) ***		11.068	(.679) ***					10.993	(.675) ***		12.598	(.712) ***		11.643	(.699) ***
S (Saskatchewan)		11.739	(.654) ***		11.725	(.652) ***		11.732	(.649) ***					13.269	(.681) ***		12.199	(.668) ***
T (Alberta)		11.071	(.636) ***		11.103	(.639) ***		11.116	(.634) ***		11.018	(.636) ***					11.495	(.660) ***
V (British Columbia)		11.298	(.647) ***		11.317	(.647) ***		11.328	(.642) ***		11.229	(.644) ***		12.901	(.671) ***			
3-Character Postal Code (FSA)																		
	M1B	.220	(1.264)	N6A	-.734	(1.282)	R3E	-1.010	(1.293)	S4N	10.856	(.801) ***	T2E	.229	(1.394)	V2L	-8.349	(1.232) ***
	M1L	12.101	(.845) ***	N6B	11.218	(.639) ***	R3J	-1.077	(1.318)	S4S	1.126	(1.326)	T2G	-1.506	(1.389)	V2S	-.297	(1.155)
	M1X	-.376	(1.185)	N6E	9.921	(.684) ***	R3T	-.640	(1.082)	S7H	-.759	(1.306)	T2J	-.776	(1.351)	V2T	11.566	(.708) ***
	M2R	11.699	(.756) ***	N6G	-.604	(1.083)	R3Y	11.082	(.676) ***	S7K	-.395	(1.313)	T2M	-1.113	(1.360)	V2Y	11.867	(.663) ***
	M3B	-.997	(1.304)	N6L	-1.493	(1.378)				S7N	11.718	(.644) ***	T2N	12.971	(.701) ***	V3A	-.413	(1.054)
	M3C	-.637	(1.170)	N6M	11.241	(.689) ***				S9H	-.691	(1.324)	T2P	-1.101	(1.166)	V3J	12.159	(.670) ***
	M3J	11.362	(.636) ***										T2R	-1.664	(1.405)	V3K	-.950	(1.392)
	M5A	.300	(1.383)										T5J	13.420	(.679) ***	V3M	12.439	(.652) ***
	M5B	-1.246	(1.364)										T5K	.534	(1.356)	V3W	-.195	(1.451)
	M5G	12.353	(.665) ***										T5S	12.700	(.706) ***	V4G	11.695	(.668) ***
	M5H	-1.236	(1.091)										T6B	-1.682	(1.324)	V4M	-.602	(1.360)
	M5S	-1.065	(1.101)										T6C	-1.247	(1.347)	V4N	-.455	(1.381)
	M5T	-.687	(1.182)										T6E	12.731	(.699) ***	V4W	-.794	(1.341)
	M6J	12.504	(.712) ***										T6G	12.684	(.690) ***	V4X	-.207	(1.455)
	M6K	11.523	(.663) ***										T6H	-.822	(1.401)	V5A	-8.263	(1.200) ***
	M6N	-1.162	(1.178)										T6N	11.951	(.682) ***	V5G	-1.333	(1.232)
	M6P	-7.197	(1.234) ***													V5J	11.613	(.726) ***
	M6R	-.865	(1.346)													V5Y	11.286	(.675) ***
	M9C	11.236	(.651) ***													V5Z	12.378	(.710) ***
	M9L	12.095	(.661) ***													V6B	12.589	(.654) ***
	M9V	-1.342	(1.290)													V6C	.800	(1.310)
	M9W	11.506	(.633) ***													V6E	12.291	(.876) ***
																V6G	1.110	(1.159)
																V6H	.133	(1.291)
																V6J	-.248	(1.127)
																V6N	12.806	(.675) ***
																V6P	11.444	(.783) ***
																V6R	-.443	(1.123)
																V6S	11.425	(.695) ***
																V6T	11.947	(.682) ***
																V6V	11.941	(.670) ***
																V6X	-.180	(1.138)
																V7A	-.452	(1.332)
																V7H	-.462	(1.431)
																V7M	-.446	(1.162)
																V7N	-5.196	(1.316) ***
																V7P	-4.439	(1.307) ***
																V7V	11.916	(.699) ***
																V7Y	11.233	(.748) ***
																V8L	.747	(1.273)
																V8M	.611	(1.288)
																V8P	-4.637	(1.343) ***
																V8R	.536	(1.369)
																V8T	9.368	(.957) ***
																V8X	8.735	(.916) ***
																V8Z	12.591	(.666) ***
Technology Fixed Effects		Incl.			Incl.			Incl.			Incl.			Incl.			Incl.	
Year Fixed Effects		Incl.			Incl.			Incl.			Incl.			Incl.			Incl.	
Inverse Mills Ratio		-1.837	(.116) ***		-1.853	(.113) ***		-1.844	(.112) ***		-1.853	(.111) ***		-1.851	(.116) ***		-1.934	(.132) ***
Constant		-9.903	(.757) ***		-9.944	(.755) ***		-9.955	(.752) ***		-9.815	(.752) ***		-11.566	(.792) ***		-10.517	(.775) ***
Log-Likelihood		-662.86			-664.57			-665.40			-664.92			-663.35			-659.72	
Likelihood Ratio Test (df)		41.0			37.6			35.9			36.9			40.0			47.3	

Note: + p<.10, * p<.05, ** p<.01, *** p<.001. The Sample included 2211 annual observations.

Table 3. FSA and Firm Characteristics

	Inventive FSAs						Uninventive FSAs				
	FSA Total Other Firms			Average Firm			FSA Total Other Firms		Average Firm		
Variable	Mean	S.D.		Mean	S.D.		Mean	S.D.	Mean	S.D.	
Patent Applications Past 5 Years	4.12	9.81	***	1.92	6.30	***	.18	2.21	.23	2.30	
Age	14.18	15.23		14.07	19.49		16.25	17.50	16.42	19.34	*
R&D Expenditures/1,000,000	6.88	14.60		3.38	9.29		4.72	50.08	4.35	45.69	
R&D Employees	66.08	111.27	*	30.70	70.09	***	10.22	66.62	14.36	69.95	
Revenues/1,000,000	72.64	238.69		29.76	132.49		14.62	92.74	17.90	99.46	
Financing/1,000,000	3.17	13.61	***	1.06	6.88	***	.20	1.85	.13	1.24	
IRAP/1,000	7.99	3.25	***	3.87	2.15	***	.30	5.77	1.26	11.75	
Spinoff	.18	.48	***	.11	.31	***	.02	.15	.03	.18	
Parent	.68	1.23	***	.20	.40	***	.12	.33	.16	.37	
TMT Size	9.85	10.68	**	3.29	1.19	***	2.18	2.87	2.89	1.18	
University Alliance	1.16	1.69	***	.64	.97	***	.22	.52	.46	.89	
Upstream Alliance	1.18	1.97	***	.63	1.02	***	.21	.46	.56	1.22	
Downstream Alliance	1.57	1.93	***	1.45	3.07	*	.28	.53	1.31	4.47	
Biotechnology Alliance	1.08	1.63	***	.48	1.03	***	.16	.42	.25	.65	
Number of Firms	3.04	3.27	***	--			.75	.95	--		
Number Same Focus Firms	.79	1.54	***	--			.17	.46	--		
Focus Concentration	.56	.35	***	--			.44	.46	--		
Number of Universities	.18	.39	***	--			.08	.27	--		
Number of Businesses/1,000	1.34	1.20	***	--			.98	.91	--		
Number of FSAs	83						222				

Note: Inventive or uninventive mean significantly larger at: * p<.05, ** p<.01, *** p<.001

Table 4. Firm Characteristics in Inventive FSAs

	Inventive Firm			**Uninventive Firm**			
Variable	Mean	S.D.		Mean	S.D.		Vs. uninventive FSA firms
Patent Applications Past 5 Years	3.68	8.42	***	0.07	0.29		
Age	14.24	19.76		13.89	19.21		
R&D Expenditures/1,000,000	5.00	11.63	***	1.67	5.41		
R&D Employees	39.88	79.10		21.02	57.63		
Revenues/1,000,000	33.68	105.54		25.61	155.95		
Financing/1,000,000	1.48	7.59	**	0.62	6.01		***
IRAP/1,000	6.12	28.19		1.50	10.12		
Spinoff	0.19	0.39	***	0.03	0.18		***
Parent	0.16	0.37		0.25	0.43	***	***
TMT Size	3.48	1.15	***	3.09	1.20		***
University Alliance	0.68	0.94	***	0.60	0.99		***
Upstream Alliance	0.81	1.13	***	0.45	0.84		
Downstream Alliance	1.52	2.33	*	1.38	3.70		
Biotechnology Alliance	0.54	0.95	***	0.42	1.10		***
Number of FSAs				83			

Note: Inventive or uninventive mean significantly larger at: * p<.05, ** p<.01, *** p<.001

Table 5. Adjacency to Inventive FSAs

		Number of Adjacent Inventive FSAs			
		0	1	2	3
Montreal	Inventive FSAs:	16%	26%	26%	32%
	Uninventive FSAs:	17%	42%	33%	8%
Greater Toronto	Inventive FSAs:	20%	67%	13%	0%
	Uninventive FSAs:	68%	18%	14%	0%
Vancouver	Inventive FSAs:	25%	19%	44%	12%
	Uninventive FSAs:	47%	42%	11%	0%
Mean	Inventive FSAs:	20%	37%	28%	15%
	Uninventive FSAs:	44%	34%	19%	3%

Table 6. Inventive FSA Characteristics by Location

	Vancouver									
	FSA Total Other Firms					Average Firm				
Variable	Mean	S.D.	Vs. Vancouver Uninventive	Vs. Toronto Inventive	Vs. Montreal Inventive	Mean	S.D.	Vs. Vancouver Uninventive	Vs. Toronto Inventive	Vs. Montreal Inventive
Patent Applications Past 5 Years	1.39	2.29	***			.93	1.91	***		
Age•	6.66	4.06				6.02	5.26	-		
R&D Expenditures/1,000,000	3.10	3.97	***		**	1.73	2.81	***		
R&D Employees	29.82	28.59	*			16.26	19.83			
Revenues/1,000,000	2.81	5.36				1.97	4.56			
Financing/1,000,000	2.20	8.33	**			1.20	5.83	*		
IRAP/1,000	11.30	37.25				6.11	29.59			
Spinoff	.59	.72	***	***	***	.32	.47	***	***	***
Parent	.00	.00	---			.00	.00	---		
TMT Size	6.23	4.46	***		**	3.62	1.01	***		***
University Alliance	1.14	.96	***	***	***	1.12	1.13	***	***	***
Upstream Alliance	.87	.76	***	***	**	1.15	1.30	***	***	***
Downstream Alliance	.84	1.05	***			.77	1.12	***		
Biotechnology Alliance	.48	.72	***			.33	.60	***		
Number of Firms	1.77	1.25	***		**	--				
Number Same Focus Firms	.51	.97	***			--				
Focus Concentration	.62	.37	***		**	--				
Number of Universities	.12	.33	***	**	**	--				
Number of Businesses/1,000	1.06	.92	-			--				
Number of FSAs	10									

	Toronto									
	FSA Total Other Firms					Average Firm				
Variable	Mean	S.D.	Vs. Toronto Uninventive	Vs. Vancouver Inventive	Vs. Montreal Inventive	Mean	S.D.	Vs. Toronto Uninventive	Vs. Vancouver Inventive	Vs. Montreal Inventive
Patent Applications Past 5 Years	8.96	17.21	***	***	**	3.40	11.02	***	**	
Age•	18.98	20.77		**		20.87	24.54		**	
R&D Expenditures/1,000,000	14.84	24.38	---	**	**	6.87	15.58		**	
R&D Employees	99.18	134.13				45.46	89.21			
Revenues/1,000,000	174.55	290.26				73.44	167.49			
Financing/1,000,000	7.43	22.42				1.61	9.82			
IRAP/1,000	2.82	23.45				3.26	24.10			
Spinoff	.09	.32	***		*	.06	.23	***		
Parent	.63	.75	***	***	**	.23	.42	***	***	
TMT Size	11.69	8.33	***	***	***	3.71	1.04	***		***
University Alliance	.89	1.01	***		**	.51	.92	***		
Upstream Alliance	.74	1.01	***		***	.38	.85	---		
Downstream Alliance	2.00	1.67	***	***	***	2.28	4.88	***	***	***
Biotechnology Alliance	1.16	1.17	***	***	***	.66	1.12	***	***	
Number of Firms	3.18	2.19	***	***	***	--				
Number Same Focus Firms	1.00	1.33	***	***	***	--				
Focus Concentration	.65	.30	***	**	***	--				
Number of Universities	.10	.31	***		*	--				
Number of Businesses/1,000	2.00	1.64	***	***	***	--				
Number of FSAs	15									

	Montreal									
	FSA Total Other Firms					Average Firm				
Variable	Mean	S.D.	Vs. Montreal Uninventive	Vs. Vancouver Inventive	Vs. Toronto Inventive	Mean	S.D.	Vs. Montreal Uninventive	Vs. Vancouver Inventive	Vs. Toronto Inventive
Patent Applications Past 5 Years	1.54	4.21	***			2.25	5.05	***	***	
Age•	12.83	15.20				12.71	20.22			
R&D Expenditures/1,000,000	1.81	3.69	***			3.42	8.13	**	*	
R&D Employees	22.88	36.94				31.62	84.45			
Revenues/1,000,000	13.12	30.40				10.09	24.83			
Financing/1,000,000	4.01	16.34				1.76	9.88			
IRAP/1,000	1.25	10.47				1.61	13.36			
Spinoff	.06	.24	***			.06	.23			
Parent	.52	.91	***	***		.31	.46	***	***	**
TMT Size	4.39	4.56	***			2.98	1.14			
University Alliance	.75	.94	***			.84	1.06	***		***
Upstream Alliance	.51	.70	***			.74	.89	***		***
Downstream Alliance	.82	1.08	***			1.42	2.17	***		
Biotechnology Alliance	.58	1.00	***	**		.62	1.76	***	***	
Number of Firms	1.44	1.38	***			--				
Number Same Focus Firms	.52	1.19	***			--				
Focus Concentration	.58	.42	***			--				
Number of Universities	.08	.28	---			--				
Number of Businesses/1,000	1.09	.60	***			--				
Number of FSAs	16									

Note: •Age is average age of other firms for FSAs. Mean significantly larger at: * p<.05, ** p<.01, *** p<.001. Mean significantly smaller at: - p<.05, -- p<.01, ---

Table 7. Inventive FSAs, Inventive and Uninventive Firm Characteristics by Location

Vancouver

	Inventive Firms					**Uninventive Firms**				
Variable	Mean	S.D.	Vs. Vancouver Uninventive	Vs. Toronto Inventive	Vs. Montreal Inventive	Mean	S.D.	Vs. Vancouver Uninventive	Vs. Toronto Inventive	Vs. Montreal Inventive
Patent Applications Past 5 Years	1.66	2.42	***			0.16	0.50		***	***
Age	4.02	2.55				8.13	6.46	**		
R&D Expenditures/1,000,000	1.49	2.08				1.99	3.41			***
R&D Employees	18.52	21.67				13.87	17.55			
Revenues/1,000,000	2.34	4.58				1.59	4.54			
Financing/1,000,000	0.90	2.34				1.51	8.03			
IRAP/1,000	8.97	38.18				3.09	16.12			
Spinoff	0.47	0.50	***	***	***	0.16	0.37		***	***
Parent	0.00	0.00				0.00	0.00			
TMT Size	3.91	1.01	***		***	3.31	0.92			***
University Alliance	1.24	1.17	**	***	***	1.00	1.09		***	
Upstream Alliance	1.43	1.24	***	***		0.85	1.30		***	***
Downstream Alliance	0.62	0.93				0.93	1.27	***		
Biotechnology Alliance	0.28	0.56				0.38	0.65	***	***	
Number of FSAs	10									

Toronto

	Inventive Firms					**Uninventive Firms**				
Variable	Mean	S.D.	Vs. Toronto Uninventive	Vs. Vancouver Inventive	Vs. Montreal Inventive	Mean	S.D.	Vs. Toronto Uninventive	Vs. Vancouver Inventive	Vs. Montreal Inventive
Patent Applications Past 5 Years	6.67	14.81	*			0.06	0.24			***
Age	26.15	27.43		*		15.47	19.87			
R&D Expenditures/1,000,000	11.92	19.62		*		1.71	6.79			*
R&D Employees	72.99	112.71				17.30	39.79			
Revenues/1,000,000	107.65	187.54				38.45	136.19			
Financing/1,000,000	2.77	13.55				0.42	2.32			
IRAP/1,000	6.44	33.65				0.00	0.00			
Spinoff	0.09	0.29	***			0.02	0.15			***
Parent	0.19	0.40		***		0.27	0.44	***	***	
TMT Size	3.84	1.16	***		***	3.58	0.88		***	***
University Alliance	0.57	0.98	***			0.44	0.86			
Upstream Alliance	0.46	0.95	***			0.31	0.73			
Downstream Alliance	1.83	1.94		***		2.74	6.63		**	*
Biotechnology Alliance	1.05	1.36	***	***	***	0.26	0.56			
Number of FSAs	15									

Montreal

	Inventive Firms					**Uninventive Firms**				
Variable	Mean	S.D.	Vs. Montreal Uninventive	Vs. Vancouver Inventive	Vs. Toronto Inventive	Mean	S.D.	Vs. Montreal Uninventive	Vs. Vancouver Inventive	Vs. Toronto Inventive
Patent Applications Past 5 Years	4.43	6.39	***	*		0.01	0.11			
Age	10.64	16.59				14.83	23.28			
R&D Expenditures/1,000,000	6.33	10.66	*			0.44	0.52			
R&D Employees	54.06	114.28				8.60	9.07			
Revenues/1,000,000	14.87	32.33				5.18	11.69			
Financing/1,000,000	1.81	5.80				1.72	12.83			
IRAP/1,000	3.19	18.69				0.00	0.00			
Spinoff	0.11	0.32	***		***	0.00	0.00			
Parent	0.31	0.47		***	***	0.31	0.46		***	***
TMT Size	3.18	1.09	***			2.78	1.17			
University Alliance	0.75	0.89			***	0.92	1.21	**		***
Upstream Alliance	0.89	0.97	**		***	0.59	0.78			***
Downstream Alliance	1.69	2.34	**	***		1.14	1.95			
Biotechnology Alliance	0.38	0.83		***		0.87	2.34	**	***	***
Number of FSAs	16									

Note: Mean significantly larger at: * p<.05, ** p<.01, *** p<.001

Table A1. Descriptive Statistics

Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28
1 Patent 5 Years	1.032	4.725																												
2 Ln(Age)	2.305	.962	.06																											
3 Ln(R&D Expenditures)	10.938	5.272	.13	.09																										
4 Ln(R&D Employees)	2.073	1.200	.28	.18	.36																									
5 ln(Revenue)	12.076	5.902	.04	.44	.24	.13																								
6 Ln(Totfin)	.904	3.594	.17	-.13	.05	.10	-.14																							
7 Ln(IRAP)	.398	2.021	.02	-.19	.04	.05	-.08	.04																						
8 Spin-Off	.070	.255	.08	-.30	.09	.11	-.15	.26	.27																					
9 Parent	.180	.384	.09	.15	.04	.13	.02	-.08	-.02	-.11																				
10 TMT Size	3.079	1.204	.14	.15	.28	.31	.18	.08	.03	.04	.05																			
11 University Alliance	.546	.934	.05	-.13	.13	.06	-.11	.12	.11	.17	.01	.09																		
12 Upstream Alliance	.592	1.129	.03	-.06	.10	.07	-.04	.06	.07	.09	-.08	.06	.29																	
13 Downstream Alliance	1.375	3.869	.05	.08	.05	.10	.11	.02	-.02	-.03	.07	.08	.02	.05																
14 Biotechnology Alliance	.359	.858	.08	.04	.12	.15	.07	.08	.07	.02	.08	.10	.12	.04	.05															
15 A (Newfoundland)	.013	.112	-.02	-.06	-.01	-.04	.00	-.03	.02	.03	.01	-.05	.01	.03	-.04	.08														
16 B (Nova Scotia)	.045	.208	-.04	-.03	-.02	-.08	.00	-.05	.03	.02	-.07	.01	-.02	.06	.03	-.02	-.02													
17 C (Prince Edward Island)	.010	.101	-.02	.01	.01	-.02	.05	-.03	.07	-.03	.01	.02	.04	-.05	.02	-.01	-.01	-.02												
18 E (New Brunswick)	.017	.128	-.03	.07	.00	-.02	.02	-.03	-.03	-.04	-.05	-.04	-.08	.09	-.04	-.03	-.01	-.03	-.01											
19 G (Quebec - East)	.070	.255	-.04	-.02	.02	-.03	-.02	-.05	-.04	-.05	-.09	-.15	-.08	-.02	-.01	-.08	-.03	-.06	-.03	-.04										
20 H (Montreal)	.132	.339	.03	.00	.01	.21	-.02	.05	-.03	-.01	.08	-.02	.05	.01	-.02	.04	-.04	-.08	-.04	-.05	-.11									
21 J (Quebec - West)	.079	.269	-.06	-.01	-.04	-.14	.04	-.07	-.04	-.04	-.07	-.06	-.05	-.06	-.07	-.02	-.03	-.06	-.03	-.04	-.08	-.11								
22 K (Ontario - Southeast)	.033	.178	.04	.00	-.03	-.01	-.01	-.01	.08	.06	.02	.05	.03	-.01	.00	-.02	-.02	-.04	-.02	-.02	-.05	-.07	-.05							
23 L (Ontario - South Central)	.122	.327	.03	.10	.04	.00	.11	.03	-.07	-.10	.07	.13	-.05	-.05	.09	-.03	-.04	-.08	-.04	-.05	-.10	-.15	-.11	-.07						
24 M (Toronto)	.102	.302	.12	.06	.06	.08	.01	.04	-.01	.00	.05	.09	.01	-.05	.05	.11	-.04	-.07	-.03	-.04	-.09	-.13	-.10	-.06	-.13					
25 N (Ontario - Southwest)	.053	.225	-.05	.11	-.01	.01	-.05	-.04	.01	-.07	.05	-.01	.09	.13	-.03	.01	-.03	-.05	-.02	-.03	-.07	-.09	-.07	-.04	-.09	-.08				
26 R (Manitoba)	.015	.123	-.02	-.02	.02	.05	-.08	-.03	.02	-.03	.08	-.09	-.01	-.06	.22	.00	-.01	-.03	-.01	-.02	-.03	-.05	-.04	-.02	-.05	-.04	-.03			
27 S (Saskatchewan)	.047	.211	-.03	-.06	-.01	-.05	.02	-.03	.04	-.06	.08	.02	.05	.12	.01	.05	-.03	-.05	-.02	-.03	-.06	-.09	-.06	-.04	-.08	-.07	-.05	-.03		
28 T (Alberta)	.084	.278	.06	-.04	.00	.06	.00	.00	.03	.12	.00	.02	-.04	-.04	-.05	-.03	-.03	-.07	-.03	-.04	-.08	-.12	-.09	-.06	-.11	-.10	-.07	-.04	-.07	
29 V (British Columbia)	.179	.384	-.05	-.11	-.05	-.09	-.07	.08	.03	.13	-.12	-.01	.05	-.02	-.07	-.03	-.05	-.10	-.05	-.06	-.13	-.18	-.14	-.09	-.17	-.16	-.11	-.06	-.10	-.14

The sample included 2211 annual observations. Correlations > |.04| significant at p<.05.

Table A2. Robust Negative Binomial Models of Patent Application Rates: First Postal Code Character

	Model 1		**Model 2**		**Model 3**	
Variable	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Patent 5 Years	.026	(.006) ***	.023	(.006) ***	.023	(.006) ***
Ln(Age)	-.005	(.069)	-.104	(.083)	-.104	(.083)
Ln(R&D Expenditures)	.007	(.011)	.009	(.011)	.009	(.011)
Ln(R&D Employees)	.096	(.060) *	.046	(.056)	.046	(.056)
ln(Revenue)	.016	(.009) *	.005	(.009)	.005	(.009)
Ln(Totfin)	.023	(.009) **	.014	(.009) +	.014	(.009) +
Ln(IRAP)	-.002	(.019)	-.008	(.017)	-.008	(.017)
Spin-Off	.031	(.198)	.204	(.180)	.204	(.180)
Parent	.348	(.250) +	.257	(.164) +	.257	(.164) +
TMT Size	.072	(.064)	.056	(.059)	.056	(.059)
University Alliance	.039	(.094)	-.003	(.089)	-.003	(.089)
Upstream Alliance	-.113	(.062) *	-.118	(.058) *	-.118	(.058) *
Downstream Alliance	-.053	(.032) *	-.048	(.031) +	-.048	(.031) +
Biotechnology Alliance	-.125	(.045) **	-.132	(.051) **	-.132	(.051) **
Postal Code						
A (Newfoundland)						
B (Nova Scotia)			5.586	(.927) ***	5.201	(.840) ***
C (Prince Edward Island)			5.387	(.744) ***	5.003	(.668) ***
E (New Brunswick)			-4.687	(.603) ***		***
G (Quebec - East)			5.394	(.752) ***	5.009	(.682) ***
H (Montreal)			5.759	(.772) ***	5.375	(.706) ***
J (Quebec - West)			4.819	(.786) ***	4.434	(.717) ***
K (Ontario - Southeast)			5.845	(.796) ***	5.460	(.733) ***
L (Ontario - South Central)			6.415	(.783) ***	6.031	(.703) ***
M (Toronto)			5.770	(.760) ***	5.385	(.702) ***
N (Ontario - Southwest)			4.760	(.805) ***	4.375	(.744) ***
R (Manitoba)			5.239	(.768) ***	4.854	(.708) ***
S (Saskatchewan)			5.889	(.786) ***	5.505	(.693) ***
T (Alberta)			5.263	(.793) ***	4.879	(.728) ***
V (British Columbia)			5.481	(.757) ***	5.097	(.689) ***
Technology Fixed Effects	Incl.		Incl.		Incl.	
Year Fixed Effects	Incl.		Incl.		Incl.	
Inverse Mills Ratio	-1.994	(.150) ***	-1.848	(.112) ***	-1.848	(.112) ***
Constant	1.648	(.398) ***	-4.109	(.857) ***	-3.724	(.807) ***
Log-Likelihood	-683.38		-666.24		-666.24	
Likelihood Ratio Test (df)			34.3 (14)	***	34.3 (13)	

Note: + p<.10, * p<.05, ** p<.01, *** p<.001. The Sample included 2211 annual observations.

Table A3. Robust Negative Binomial Models of Patent Application Rates: First Two Postal Code Characters

	B (Nova Scotia)			C (Prince Edward Island)			G (Quebec - East)			H (Montreal)			J (Quebec - West)			K (Ontario - Southeast)			L (Ontario - South Central)		
Variable	Coef.	S.E.		Coef.	S.E.		Coef.	S.E.		Coef.	S.E.		Coef.	S.E.		Coef.	S.E.		Coef.	S.E.	
Patent 5 Years	.023	(.006)	***	.023	(.006)	***	.023	(.006)	***	.022	(.006)	***	.023	(.006)	***	.023	(.007)	***	.025	(.006)	***
Ln(Age)	-.104	(.083)		-.104	(.083)		-.104	(.083)		-.110	(.083)	+	-.103	(.083)		-.098	(.091)		-.049	(.093)	
Ln(R&D Expenditures)	.009	(.011)		.009	(.011)		.009	(.011)		.009	(.011)		.009	(.011)		.011	(.011)		.006	(.012)	
Ln(R&D Employees)	.046	(.056)		.046	(.056)		.047	(.056)		.066	(.056)		.047	(.056)		.048	(.064)		.027	(.051)	
ln(Revenue)	.005	(.009)		.005	(.009)		.005	(.009)		.006	(.010)		.005	(.009)		.004	(.009)		.005	(.010)	
Ln(Totfin)	.015	(.009)	+	.014	(.009)	+	.014	(.009)	+	.014	(.010)	+	.014	(.009)	+	.014	(.009)	+	.016	(.010)	*
Ln(IRAP)	-.008	(.017)		-.008	(.017)		-.008	(.017)		-.003	(.017)		-.008	(.017)		-.008	(.017)		-.008	(.016)	
Spin-Off	.199	(.179)		.204	(.180)		.203	(.179)		.136	(.184)		.203	(.179)		.253	(.185)	+	.190	(.190)	
Parent	.256	(.163)	+	.257	(.164)	+	.258	(.164)	+	.285	(.161)	*	.257	(.164)	+	.276	(.166)	*	-.030	(.166)	
TMT Size	.056	(.059)		.056	(.059)		.056	(.058)		.068	(.061)		.055	(.059)		.049	(.060)		.030	(.056)	
University Alliance	-.005	(.089)		-.003	(.089)		-.004	(.089)		.022	(.093)		-.003	(.089)		.017	(.091)		.040	(.092)	
Upstream Alliance	-.116	(.057)	*	-.118	(.058)	*	-.118	(.058)	*	-.104	(.055)	*	-.118	(.058)	*	-.113	(.058)	*	-.148	(.059)	**
Downstream Alliance	-.048	(.031)	+	-.048	(.031)	+	-.048	(.031)	+	-.062	(.032)	*	-.048	(.031)	+	-.045	(.031)	+	-.038	(.030)	
Biotechnology Alliance	-.131	(.051)	**	-.132	(.051)	**	-.131	(.051)	**	-.137	(.051)	**	-.131	(.051)	**	-.127	(.051)	**	-.119	(.047)	**
1-Character Postal Code																					
B (Nova Scotia)				4.412	(.834)	***	4.269	(.834)	***	4.495	(.839)	***	5.050	(.837)	***	5.726	(.856)	***	5.619	(.800)	***
C (Prince Edward Island)	4.533	(.666)	***				4.070	(.667)	***	4.278	(.669)	***	4.854	(.672)	***	5.507	(.709)	***	5.376	(.649)	***
G (Quebec - East)	4.535	(.675)	***	4.220	(.679)	***				4.275	(.667)	***	4.861	(.686)	***	5.548	(.685)	***	5.470	(.640)	***
H (Montreal)	4.903	(.702)	***	4.586	(.706)	***	4.442	(.706)	***				5.227	(.708)	***	5.845	(.722)	***	5.858	(.668)	***
J (Quebec - West)	3.963	(.713)	***	3.646	(.716)	***	3.507	(.717)	***	3.738	(.703)	***				4.970	(.733)	***	4.881	(.677)	***
K (Ontario - Southeast)	4.986	(.733)	***	4.672	(.734)	***	4.529	(.734)	***	4.698	(.755)	***	5.311	(.738)	***				5.930	(.720)	***
L (Ontario - South Central)	5.561	(.700)	***	5.242	(.702)	***	5.102	(.704)	***	5.330	(.706)	***	5.885	(.706)	***	6.544	(.715)	***			
M (Toronto)	4.916	(.699)	***	4.596	(.702)	***	4.454	(.702)	***	4.695	(.694)	***	5.237	(.706)	***	5.879	(.724)	***	5.789	(.667)	***
N (Ontario - Southwest)	3.902	(.740)	***	3.586	(.744)	***	3.445	(.745)	***	3.591	(.743)	***	4.228	(.748)	***	4.860	(.754)	***	5.093	(.685)	***
R (Manitoba)	4.376	(.701)	***	4.065	(.706)	***	3.927	(.707)	***	4.076	(.722)	***	4.706	(.708)	***	5.386	(.716)	***	5.316	(.691)	***
S (Saskatchewan)	5.033	(.689)	***	4.716	(.694)	***	4.574	(.694)	***	4.733	(.693)	***	5.355	(.698)	***	6.008	(.705)	***	5.908	(.685)	***
T (Alberta)	4.412	(.723)	***	4.090	(.726)	***	3.949	(.726)	***	4.202	(.719)	***	4.732	(.728)	***	5.362	(.747)	***	5.388	(.690)	***
V (British Columbia)	4.626	(.685)	***	4.308	(.689)	***	4.167	(.690)	***	4.360	(.689)	***	4.949	(.690)	***	5.576	(.690)	***	5.549	(.672)	***

2-Character Postal Code

B	Coef.	S.E.		C	Coef.	S.E.		G	Coef.	S.E.		H	Coef.	S.E.		J	Coef.	S.E.		K	Coef.	S.E.		L	Coef.	S.E.	
B0	-4.229	(.778)	***	C0	-5.740	(.890)	***	G0	-3.698	(.524)	***	H1	4.875	(.692)	***	J0	-3.696	(.456)	***	K1	6.222	(.751)	***	L0	-3.533	(.989)	***
B2	-10.038	(1.302)	***	C1	4.214	(.667)	***	G1	4.107	(.687)	***	H2	4.855	(.753)	***	J1	-3.690	(.466)	***	K2	5.962	(.837)	***	L1	-5.035	(1.157)	***
B3	4.815	(.838)	***					G2	-5.450	(.713)	***	H3	4.211	(.719)	***	J2	-5.350	(.637)	***	K6	-3.771	(1.077)	***	L3	5.589	(.832)	***
B4	-4.487	(.594)	***					G6	-12.026	(1.200)	***	H4	4.616	(.742)	***	J3	-9.712	(1.229)	***	K7	5.215	(.799)	***	L4	6.172	(.687)	***
												H7	4.923	(.727)	***	J4	-5.459	(.703)	***	K9	-5.450	(1.076)	***	L5	7.001	(.714)	***
												H8	-3.962	(.857)	***	J5	-11.815	(1.216)	***					L6	-5.398	(.534)	***
												H9	4.882	(.669)	***	J7	4.345	(.715)	***					L7	5.605	(.781)	***
																J8	-5.171	(1.122)	***					L8	-4.952	(1.134)	***
																								L9	-5.526	(1.075)	***

	B (Nova Scotia)			C (Prince Edward Island)			G (Quebec - East)			H (Montreal)			J (Quebec - West)			K (Ontario - Southeast)			L (Ontario - South Central)		
Technology Fixed Effects	Incl.			Incl.			Incl.			Incl.			Incl.			Incl.			Incl.		
Year Fixed Effects	Incl.			Incl.			Incl.			Incl.			Incl.			Incl.			Incl.		
Inverse Mills Ratio	-1.849	(.112)	***	-1.848	(.112)	***	-1.845	(.112)	***	-1.815	(.112)	***	-1.847	(.112)	***	-1.844	(.116)	***	-1.813	(.108)	***
Constant	-3.260	(.800)	***	-2.935	(.804)	***	-2.793	(.804)	***	-3.026	(.803)	***	-3.569	(.807)	***	-4.282	(.823)	***	-4.184	(.746)	***
Log-Likelihood	-665.83			-666.24			-665.96			-664.05			-666.10			-665.09			-662.21		
Likelihood Ratio Test (df)	35.1 (16)		***	34.3 (14)		***	34.8 (16)		***	38.6 (19)		***	34.5 (20)		***	36.6 (17)		***	42.3 (21)		***

Note: + p<.10, * p<.05, ** p<.01, *** p<.001. The sample included 2211 annual observations.

Table A4. Robust Negative Binomial Models of Patent Application Rates: First Two Postal Code Characters

		M (Toronto)			N (Ontario - Southwest)			R (Manitoba)			S (Saskatchewan)			T (Alberta)			V (British Columbia)	
Variable		Coef.	S.E.		Coef.	S.E.		Coef.	S.E.		Coef.	S.E.		Coef.	S.E.		Coef.	S.E.
Patent 5 Years		.021	(.007) ***		.023	(.006) ***		.023	(.006) ***		.023	(.006) ***		.022	(.007) ***		.023	(.007) ***
Ln(Age)		-.087	(.086)		-.104	(.083)		-.104	(.083)		-.102	(.082)		-.096	(.083)		-.092	(.087)
Ln(R&D Expenditures)		.008	(.012)		.009	(.011)		.009	(.011)		.009	(.011)		.008	(.011)		.008	(.012)
Ln(R&D Employees)		.055	(.058)		.046	(.056)		.046	(.056)		.044	(.055)		.037	(.057)		.054	(.059)
ln(Revenue)		.005	(.010)		.005	(.009)		.005	(.009)		.004	(.010)		.003	(.009)		.004	(.010)
Ln(Totfin)		.015	(.009) *		.014	(.009) *		.014	(.009) *		.015	(.009) *		.014	(.009) *		.014	(.009) *
Ln(IRAP)		-.009	(.017)		-.008	(.017)		-.008	(.017)		-.008	(.017)		-.004	(.017)		-.012	(.018)
Spin-Off		.218	(.186)		.204	(.180)		.204	(.180)		.209	(.180)		.091	(.206)		.233	(.183)
Parent		.257	(.174) +		.257	(.164) +		.257	(.164) +		.276	(.165) *		.293	(.168) *		.261	(.165) +
TMT Size		.055	(.060)		.056	(.059)		.056	(.059)		.061	(.058)		.051	(.059)		.067	(.060)
University Alliance		.006	(.090)		-.003	(.089)		-.003	(.089)		-.008	(.089)		.018	(.093)		.005	(.090)
Upstream Alliance		-.125	(.058) *		-.118	(.058) *		-.118	(.058) *		-.109	(.057) *		-.115	(.060) *		-.122	(.059) *
Downstream Alliance		-.047	(.033) +		-.048	(.031) +		-.048	(.031) +		-.043	(.031) +		-.046	(.030) +		-.049	(.031) +
Biotechnology Alliance		-.117	(.050) **		-.132	(.051) **		-.132	(.051) **		-.137	(.050) **		-.126	(.049) **		-.134	(.051) **
1-Character Postal Code																		
B (Nova Scotia)		4.371	(.844) ***		4.285	(.835) ***		5.204	(.831) ***		5.180	(.835) ***		4.312	(.859) ***		7.057	(.666) ***
C (Prince Edward Island)		4.180	(.673) ***		4.087	(.668) ***		5.005	(.663) ***		4.976	(.673) ***		4.026	(.675) ***		6.887	(.314) ***
G (Quebec - East)		4.234	(.691) ***		4.093	(.679) ***		5.011	(.674) ***		4.996	(.677) ***		4.075	(.687) ***		6.914	(.531) ***
H (Montreal)		4.602	(.718) ***		4.459	(.707) ***		5.377	(.704) ***		5.338	(.705) ***		4.418	(.719) ***		7.269	(.565) ***
J (Quebec - West)		3.695	(.732) ***		3.519	(.717) ***		4.437	(.710) ***		4.424	(.716) ***		3.518	(.725) ***		6.342	(.508) ***
K (Ontario - Southeast)		4.660	(.744) ***		4.544	(.736) ***		5.463	(.734) ***		5.434	(.734) ***		4.517	(.741) ***		7.331	(.599) ***
L (Ontario - South Central)		5.267	(.711) ***		5.115	(.703) ***		6.033	(.699) ***		6.003	(.700) ***		5.092	(.703) ***		7.910	(.585) ***
M (Toronto)					4.469	(.702) ***		5.387	(.700) ***		5.365	(.703) ***		4.437	(.713) ***		7.268	(.548) ***
N (Ontario - Southwest)		3.606	(.761) ***					4.377	(.744) ***		4.326	(.747) ***		3.379	(.757) ***		6.255	(.547) ***
R (Manitoba)		4.064	(.717) ***		3.938	(.707) ***					4.832	(.706) ***		3.869	(.705) ***		6.732	(.677) ***
S (Saskatchewan)		4.746	(.706) ***		4.589	(.694) ***		5.507	(.690) ***					4.550	(.699) ***		7.395	(.372) ***
T (Alberta)		4.104	(.739) ***		3.963	(.727) ***		4.881	(.723) ***		4.847	(.724) ***					6.758	(.505) ***
V (British Columbia)		4.356	(.709) ***		4.181	(.690) ***		5.099	(.684) ***		5.066	(.691) ***		4.171	(.696) ***			
2-Character Postal Code																		
	M1	4.789	(.788) ***	N0	-3.547	(.675) ***	R0	-3.298	(1.611) *	S4	4.707	(.848) ***	T0	-5.205	(.633) ***	V0	-3.299	(.490) ***
	M2	4.690	(.808) ***	N1	-3.462	(.522) ***	R3	4.856	(.703) ***	S7	5.556	(.709) ***	T1	-5.527	(.734) ***	V1	-5.313	(.691) ***
	M3	4.424	(.702) ***	N2	-4.756	(.738) ***				S9	-5.298	(1.080) ***	T2	4.220	(.809) ***	V2	6.847	(.551) ***
	M4	-3.854	(.571) ***	N5	-4.102	(1.110) ***							T3	-4.365	(1.071) ***	V3	7.526	(.286) ***
	M5	5.388	(.806) ***	N6	3.459	(.745) ***							T4	-5.333	(1.065) ***	V4	6.934	(.554) ***
	M6	4.910	(.739) ***	N7	-4.762	(.811) ***							T5	4.144	(.692) ***	V5	6.922	(.457) ***
	M8	-4.807	(.790) ***	N8	-5.143	(1.076) ***							T6	3.772	(.740) ***	V6	7.041	(.584) ***
	M9	4.524	(.744) ***										T8	-4.796	(1.099) ***	V7	6.688	(.517) ***
													T9	-5.096	(1.107) ***	V8	7.456	(.615) ***
																V9	-6.294	(.874) ***
Technology Fixed Effects		Incl.			Incl.			Incl.			Incl.			Incl.			Incl.	
Year Fixed Effects		Incl.			Incl.			Incl.			Incl.			Incl.			Incl.	
Inverse Mills Ratio		-1.847	(.115) ***		-1.848	(.112) ***		-1.848	(.112) ***		-1.856	(.111) ***		-1.837	(.113) ***		-1.867	(.117) ***
Constant		-2.985	(.813) ***		-2.808	(.805) ***		-3.726	(.799) ***		-3.653	(.803) ***		-2.822	(.827) ***		-5.624	(.664) ***
Log-Likelihood		-665.38			-666.24			-666.24			-665.77			-665.51			-665.56	
Likelihood Ratio Test (df)		36.0 (20)	***		34.3 (19)	***		34.3 (14)	***		35.2 (15)	***		35.7 (21)	***		35.6 (22)	***

Note: + p<.10, * p<.05, ** p<.01, *** p<.001. The sample included 2211 annual observations.