Catalogue no. 11-622-MIE — No. 018
ISSN 1705-6896
ISBN 978-0-662-47711-2

Research Paper

## The Canadian Economy in Transition Series

# Cities and Growth: Knowledge Spillovers in the Adoption of Advanced Manufacturing Technologies

by W. Joung Yeo Angela No

Micro-economic Analysis Division
18th Floor, R.H. Coats Building, 100 Tunney's Pasture Driveway
Ottawa, K1A 0T6

Telephone: 1-800-263-1136

Statistics Canada Statistique Canada

Canada

### How to obtain more information

Specific inquiries about this product and related statistics or services should be directed to Media Hotline, Communications and Library Services Division, Statistics Canada, Ottawa, Ontario, K1A 0T6 (telephone: 613-951-4636).

For information about this product or the wide range of services and data available from Statistics Canada, visit our website at www.statcan.ca or contact us by e-mail at infostats@statcan.ca or by telephone from 8:30 a.m. to 4:30 p.m. Monday to Friday:

**Statistics Canada National Contact Centre**

Toll-free telephone (Canada and the United States):

| | |
|---|---|
| Inquiries line | 1-800-263-1136 |
| National telecommunications device for the hearing impaired | 1-800-363-7629 |
| Fax line | 1-877-287-4369 |

Local or international calls:

| | |
|---|---|
| Inquiries line | 1-613-951-8116 |
| Fax line | 1-613-951-0581 |

**Depository services program**

| | |
|---|---|
| Inquiries line | 1-800-635-7943 |
| Fax line | 1-800-565-7757 |

### Information to access the product

This product, Catalogue no. 11-622-MIE, is available for free in electronic format. To obtain a single issue, visit our website at www.statcan.ca and select “Publications.”

### Standards of service to the public

Statistics Canada is committed to serving its clients in a prompt, reliable and courteous manner. To this end, the Agency has developed standards of service which its employees observe in serving its clients. To obtain a copy of these service standards, please contact Statistics Canada toll free at 1-800-263-1136. The service standards are also published on www.statcan.ca under “About us” > “Providing services to Canadians.”

## The Canadian Economy in Transition Research Paper Series

*The Canadian Economy in Transition* is a series of new analytical reports that investigate the dynamics of industrial change in the Canadian economy. This new series brings together a coherent set of research reports that provide users with a wide variety of empirical perspectives on the economy’s changing industrial structure. These perspectives include the dynamics of productivity, profitability, employment, output, investment, occupational structure and industrial geography. Readers are encouraged to contact the authors with comments, criticisms and suggestions.

The primary distribution medium for the papers is the Internet. These papers can be downloaded from the Internet at www.statcan.ca for free.

All papers in *The Canadian Economy in Transition* series go through institutional and peer review to ensure that they conform to Statistics Canada’s mandate as a government statistical agency and adhere to generally accepted standards of good professional practice.

The papers in the series often include results derived from multivariate analysis or other statistical techniques. It should be recognized that the results of these analyses are subject to uncertainty in the reported estimates.

The level of uncertainty will depend on several factors: the nature of the functional form used in the multivariate analysis; the type of econometric technique employed; the appropriateness of the statistical assumptions embedded in the model or technique; the comprehensiveness of the variables included in the analysis; and the accuracy of the data that are utilized. The peer group review process is meant to ensure that the papers in the series have followed accepted standards to minimize problems in each of these areas.

Statistics Canada
Micro-economic Analysis Division

# Cities and Growth: Knowledge Spillovers in the Adoption of Advanced Manufacturing Technologies

W. Joung Yeo Angela No

Published by authority of the Minister responsible for Statistics Canada



February 2008

Catalogue no. 11-622-MIE, no. 018
Frequency: Occasional

ISSN 1705-6896
ISBN 978-0-662-47711-2

Cette publication est disponible en français (n° 11-622-MIF au catalogue, n° 018).

**Note of appreciation**
Canada owes the success of its statistical system to a long-standing partnership between Statistics Canada, the citizens of Canada, its businesses, governments and other institutions. Accurate and timely statistical information could not be produced without their continued cooperation and goodwill.

## *Acknowledgements*

This paper was completed by the author as part of her doctoral dissertation under the supervision of Professor D. Trefler at the University of Toronto. Access to the data was granted under the doctoral fellowship program of Statistics Canada.

# Table of contents

# *Abstract*

This paper examines the presence of knowledge spillovers that affect the adoption of advanced technologies in the Canadian manufacturing sector. It examines whether plants that adopt advanced technologies are more likely to do so when there are other nearby plants that do so within a model of technology adoption.

*Keywords:* Technology adoption, agglomeration, knowledge spillovers, micro-data

JEL classification: O3, R3

# *Executive summary*

Knowledge spillovers associated with the diffusion of new technologies have long been viewed as important drivers of economic growth. However, this claim has largely resisted econometric scrutiny because patterns of technology adoption are generally not observable. This paper overcomes the problem by exploiting a proprietary panel data set that reports the adoption of 22 advanced-manufacturing technologies by 1,902 Canadian plants. The paper starts with documenting the fact that the adoption of these technologies is more highly concentrated geographically (i.e., agglomerated) than other forms of economic activity. Motivated by this fact, it tests for knowledge spillovers by investigating how a plant's probability of adopting a new technology depends on the presence of prior adopters. The results indicate that technology adoption is facilitated by the presence of prior adopters with four characteristics. First, they are adopters of the same technology (as opposed to advanced technologies in general). Second, they reside in the same region. Third, they are similar to the potential adopter in that they purchase a similar set of intermediate goods and services. Finally, they are dissimilar to the potential adopter in that they do not operate in the same product market (i.e., the same 4-digit Standard Industrial Classification code). These results are robust when controlling for the effects of regional labour pooling, regional linkages to suppliers and buyers, as well as industry-, region-, time- and technology-fixed effects. These findings strongly suggest that knowledge spillovers are one of the driving forces of agglomeration in the adoption of new technologies.

# 1. Introduction

Knowledge spillovers associated with the diffusion of new technologies have long been viewed as important drivers of modern economic growth (Rosenberg 1982, Landes 1998 and Romer 1990). Since knowledge spillovers both facilitate and are facilitated by regional economic agglomerations (Marshall 1920, Krugman 1991a and 1991b and Porter 1998) it is natural to consider whether knowledge spillovers also lead to agglomeration effects in the adoption of new technologies. Specifically, is the adoption of new technologies more highly agglomerated than other forms of economic activity and, if so, can this be explained by localized knowledge spillovers? However, the effect of knowledge spillovers on technology adoption has not been studied in the literature. The aims of this paper are to examine whether there are localized knowledge spillovers in the adoption of new technologies and to identify and estimate the effects of knowledge spillovers.

Figure 1 provides a simple answer to the first part of this question on the agglomeration of technology adoption. It shows that geographic concentration is higher for plants using advanced manufacturing technologies than it is for all plants in an industry.[1] This fact is new to the literature and raises an obvious, but important question: What explains the higher degree of geographic agglomeration among adopters of advanced-manufacturing technologies? One potential explanation points to knowledge spillovers across technology adopters. Unfortunately, this is not an easy hypothesis to explore. First, we rarely observe knowledge spillovers directly. Second, there are alternative potential explanations such as labour pooling, forward and backward linkages between suppliers and purchasers (Krugman 1991a; Fujita, Krugman and Venables 1999 and Porter 1990) and local amenities such as transportation infrastructure and weather, which have nothing to do with spillovers.[2]

In this paper, each of these explanations is investigated. While we find some support for almost all of them, our main result is that a plant is more likely to adopt a specific technology (e.g., a flexible manufacturing cell) if that specific technology has already been adopted by other plants in ‘similar industries’ in the same region. Similar industries here represent a self-constructed set of industries that shares a similar pattern of input purchases.[3] This result cannot be traced back to a spurious correlation operating at the industry, region or industry × region levels. First, the result holds good, even after controlling for labour pooling, backward linkages to suppliers, forward linkages with buyers, and also industry-, region-, technology- and time-fixed effects. Second, the result shows that the effect is strongest with geographic, technological and functional similarities and it decays with the distance in those three dimensions. Third, the result is strongest when prior adopters are in a different industry than that of the potential adopter. In short, our findings strongly suggest the existence of communication across plants within the same geographical region.

1. We expand on this in Section 2.
2. See Hanson (2000) for discussion of the issues associated with identifying agglomeration effects.
3. Further details of the construction of similar industries are discussed in Section 4.2.

Such communication implies that there are localized, learning-based knowledge spillovers (Case 1992; Jaffe, Trajtenberg and Henderson 1993; Powell and Brantley 1992 and von Hippel 1988). For instance, in the decision to adopt a new technology, potential adopters often face uncertainties about implementation costs. Since certain types of knowledge about the implementation of a new technology are tacit, learning about tacit knowledge is more likely to happen through direct observation of early adopters, demonstration, word-of-mouth and other informal mechanisms. Hence, the local presence of prior adopters would facilitate the rapid and complete diffusion of a new technology.

The analysis in this paper is based upon a proprietary panel data set on the adoption of 22 advanced-manufacturing technologies by 1,902 Canadian plants. I use these data to address the following questions. First, and most importantly, are there regional knowledge spillovers linking prior adopters to potential adopters? If so, does the extent of spillovers depend on the similarity between prior adopters and potential adopters where 'similarity' is measured in terms of the pattern of input purchases? Second, are knowledge spillovers from prior adopters to potential adopters conditional on geographic proximity? Are the effects of knowledge spillovers from prior adopters confined to potential adopters within the same geographical region or are they extended to geographically distant ones as well? Third, are knowledge spillovers bound within technological proximity? If one plant adopts technology $\tau$, does this have any impact on other plants' adoption decision of any technology or only of technology $\tau$? Fourth, what is the sectoral scope of agglomeration externalities on technology adoption? That is, is it regional specialization in just a few industries (Marshall 1920) or regional diversification of industries (Jacobs 1970) that facilitates technology adoption?

While the effects of agglomeration on technology adoption are conjectured to be important in most discussions about agglomeration, there is very little related work. There are three relevant strands of literature. The first follows Jaffe, Trajtenberg and Henderson (1993), who studied the type of knowledge spillover that is captured by patent citations. The use of patent citations to study knowledge spillovers warrants further research on knowledge spillovers because of three particularities of patents. First, firms often do not patent (Levin et al. 1987 and Rosenberg 1982). Second, not all patents contain valuable information, hence they may not be the best measure of knowledge spillovers. Third, patents only describe a particular aspect of innovative knowledge, and not all innovative activities lend themselves to patenting. On the other hand, the 22 advanced-manufacturing technologies employed in this study do not share the above characteristics and are often general-purpose technologies that are of value and universally accessible. Consequently, they capture different aspects of knowledge than those obtained from patents, and hence they lend themselves as likely candidates for a study of knowledge spillovers and complement the literature of knowledge spillovers in a critical aspect.

The second strand in the literature is not about knowledge spillovers per se, but about the importance of different sources of agglomeration (Rosenthal and Strange 2001; Dumais, Ellison and Glaeser 1997 and Holmes 2002). These papers examined each source of agglomeration separately, but to the extent of considering knowledge spillovers, they either treated them as residuals or measured them imperfectly.

The third related strand of literature examines the impact of agglomeration on technology adoption. This literature consists of only two studies (Harrison, Kelley and Gant 1996; Kelley and Helper 1996) that examine the effects of location attributes on the adoption of computer numerically controlled (CNC) machines. As in the first and second strands, knowledge spillovers were not directly investigated nor were they isolated from the effects of other location attributes, since the goal was to examine the location attributes that better facilitated technology adoption. In addition, the literature warrants further research in this area because these are case studies in nature that are based on the adoption of one specific technology in a small number of plants in a small subset of industries—i.e., 342 plants in 21 3-digit Standard Industrial Classification (SIC) industries. Consequently, identification of the effects of knowledge spillovers is still left unanswered in the literature. This paper is aimed at overcoming these deficiencies by empirically identifying and separately estimating the impact of knowledge spillovers and other sources of agglomeration on technology adoption.

The paper's main finding is that technology adoption is facilitated by the presence of prior technology adopters with four characteristics: (1) they are adopters of the same technology, as opposed to adopters of advanced technology more generally; (2) they reside in the same geographical region; (3) they are similar to the potential adopter in that they purchase a similar set of intermediate goods and services; and (4) the effects of prior adopters are greatest if prior adopters are dissimilar to the potential adopter in that they do not operate in the same product market (i.e., the same 4-digit SIC code). This result holds good, even after controlling for the effects of regional labour pooling, regional linkages to suppliers and buyers, as well as industry-, region-, technology- and time-fixed effects. These findings are strongly indicative of the presence of localized-knowledge spillovers in the adoption of new technologies.

The remainder of this paper is organized as follows. Chapter 2 documents the higher concentration of technology-adopting plants than for all manufacturing plants. Chapter 3 discusses the methodology. Chapter 4 describes the data sources. Chapter 5 presents the results of agglomeration effects on technology adoption. Chapter 6 concludes.

## 2. The geographic concentration of advanced technology adopters

If some kind of knowledge spillovers across technology adopters are indeed present, then the technology adopters should exhibit a higher geographical concentration than plants overall. To investigate whether or not the above hypothesis is supported by the data, the degree of geographic concentrations of advanced-technology-user plants versus all plants in the manufacturing sector in Canada is examined. As a measure of the degree of agglomeration, we employ the Ellison-Glaeser index of concentration.[4] This index measures the excess concentration beyond that which would be expected to occur randomly. It takes on a value of zero when an industry is as concentrated as one would expect to result from a random location process, and assumes a positive value when an industry is concentrated more than what one would expect to occur randomly.

Figure 1 exhibits the Ellison-Glaeser index of concentration for all manufacturing plants and advanced-technology adopting plants in 1993 for 2-digit Standard Industrial Classification (SIC) manufacturing industries at the economic region level.[5] The grey bar represents the concentration by all plants in each industry. All 2-digit manufacturing industries have a positive value of the index, indicating excess geographic concentration. This excess concentration is not surprising, since the geographic concentration of economic activity is a well-documented fact in the literature (Krugman 1991b, Ellison and Glaeser 1997). What is more interesting, however, is the degree of concentration among adopters of advanced technologies, which is indicated by the black bars. It shows that technology adopters not only exhibit excessive concentration in every industry, but are substantially more concentrated than the overall number of plants for most industries. This fact has never been documented in the literature.[6] While a positive value of the index is not sufficient evidence for the presence of knowledge spillovers among technology adopters, it is a necessary evidence of them. What then would be the explanation for the higher degree of agglomeration among technology adopters? Is it localized-knowledge spillovers across

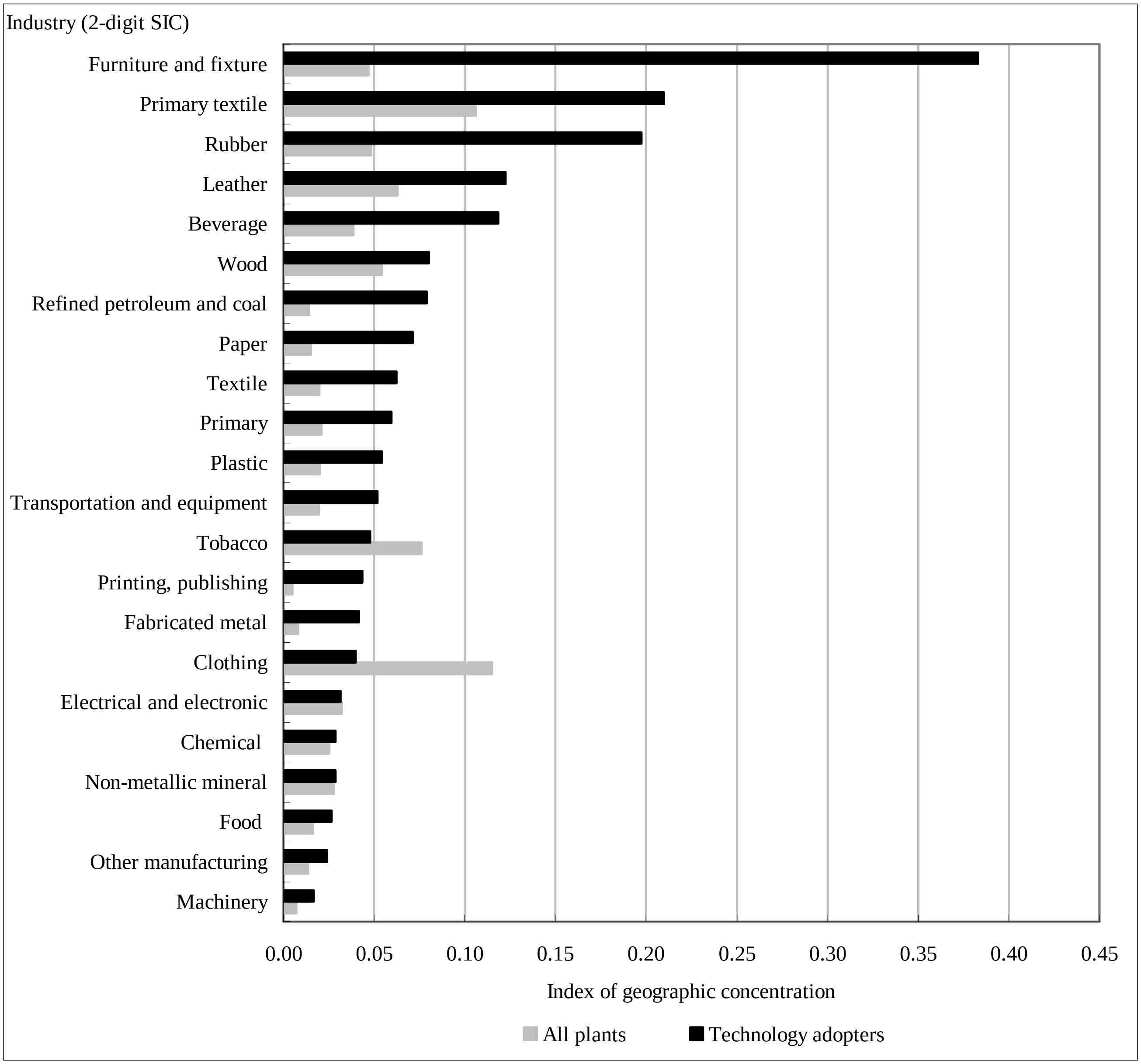
---

4. The Ellison-Glaeser index is defined as $\gamma \equiv \dfrac{G-H}{1-H} \equiv \dfrac{\sum_{i=1}^{M}(s_i - x_i)^2 \Big/ \left(1-\sum_{i=1}^{M} x_i^2\right) - \sum_{j=1}^{N} z_j^2}{1-\sum_{j=1}^{N} z_j^2}$.

   $G \equiv \sum_i \left(s_i - x_i\right)^2$ is the spatial Gini coefficient, where $x_i$ is location *i*'s share of employment in a particular industry. $H = \sum_{j=1} z_j^2$ is the Herfindahl index of the *j* plants in the industry, with $z_j$ representing the employment share of the *j*th plant. Let $s_1, s_2, \ldots, s_M$ be the shares of an industry's employment in each of *M* geographic areas, and $x_1, x_2, \ldots, x_M$ be the shares of total employment in each of *M* areas. It corrects for the random concentration arising from industrial structure that the spatial Gini does not control for.
5. See Section 5.2 for a more detailed explanation on economic regions.
6. Audretch and Feldman (1996) show that innovative activity is substantially more concentrated than overall production, and industries that emphasize research and development tend to be more spatially concentrated. A related result is obtained by Jaffe, Trajtenberg and Henderson (1993), who show that patent citations are highly spatially concentrated.

technology-adopting plants, or alternatively, is it other agglomeration economies or ‘common environment’ effects that attract plants to certain regions that also facilitate technology adoption?

**Figure 1**
**Geographic concentration of activity, all plants and advanced-technology adopters, Canada, 1993**




Note: SIC stands for Standard Industrial Classification. This figure shows results of the author’s calculations using the Ellison-Glaeser index of concentration.
Sources: Statistics Canada, 1993 Survey of Innovation and Advanced Technology, and Annual Survey of Manufactures.

# 3. Methodology

## 3.1 Conceptual framework

There has been an increasing emphasis on the role of the agglomeration of economic activities. Over history, we have witnessed that industries tend to geographically concentrate in a few regions, and this pattern of concentration has not ceased to increase, even in an era of low transportation and communication costs. The degrees of regional concentration of industries are simply too great to be explained by historical accident or random process (Ellison and Glaeser 1997). The high concentrations of economic activities are thus believed to be driven by the advantages that regional-agglomeration economies have to offer. The three most widely acknowledged advantages of regional agglomeration are knowledge spillovers; specialized, skilled labour; and input sharing (Marshall 1920). While the effects of specialized, skilled labour and input sharing can be relatively easily measured with accuracy, estimating the effects of knowledge spillovers has resisted econometric scrutiny, mainly because of its unobservable nature in most cases.

There are two types of knowledge: one is explicit or codified knowledge that can be effectively expressed using symbolic forms of representation; the other is tacit knowledge that defies such representation (Reber 1995). The more easily explicit knowledge can be accessed, the more critical a role does tacit knowledge play in sustaining and enhancing the competitive position of the firm (Maskell and Malmberg 1999). Consequently, tacit knowledge now plays a greater role than ever at a time when explicit knowledge has become easier to obtain.

When implementing new technologies, plants face many kinds of uncertainties associated with the costs and benefits of technologies, adaptation difficulties and employee training. More information on these would not only reduce the uncertainties associated with adopting new technologies but would also enable plants to better assess risks and expectations. However, because some types of information associated with technology implementations are tacit—for example, detailed engineering characteristics or particular organizational changes to fully exploit technology capabilities—learning this type of knowledge depends on direct observation of early adopters, demonstration, word-of-mouth and other informal mechanisms. Therefore, the local presence of prior adopters may facilitate interplant-knowledge spillovers in the region. Furthermore, the feedback loop of knowledge spillovers from technology adopters facilitates, and is facilitated by, regional agglomeration (Case 1992; Jaffe, Trajtenberg and Henderson 1993; Powell and Brantley 1992; and von Hippel 1988).

Therefore, we can think of the local presence of prior adopters of technology as a measure of a source of information that is difficult to obtain from a distance. Consequently, we will refer to the positive impact resulting from the local presence of prior adopters of technology as knowledge spillovers from prior adopters to potential adopters.

## 3.2 Empirical framework

Can data on the pattern of technology adoption reveal whether a plant's adoption decision is affected by the presence of prior adopters of technology around it? To explain the methodology for estimating the impact of the local presence of prior adopters of technology, we first begin by modelling the probability of a plant's technology-adoption decision. Let us suppose that the true model governing the technology adoption of a plant is given by

$$\Pr(Adoption_{p\tau irt}) = f\,(KnoweldgeSpillover_{\tau irt}, plant\ characteristics_p, controls)$$

where $p$ indexes plant, $i$ indexes industry, $r$ indexes region, $\tau$ indexes technology and $t$ indexes time. $Adoption_{p\tau irt}$ is a binary variable indicating whether a plant $p$ in industry $i$ in region $r$ adopts technology $\tau$ at time $t$.

Because knowledge spillover is unobservable, and thus needs to be inferred, the central task in estimating knowledge spillover lies in how accurately we can specify the channel of knowledge spillovers and how finely we can control for exogenous effects that influence a plant's probability of technology adoption. By estimating the impact of the local presence of technology adopters on other plants' probability of technology adoption, this paper attempts to identify the knowledge spillovers from prior adopters to potential adopters. The preliminary results show that the presence of prior adopters positively affects technology adoption by other plants. Detailed results are discussed in Chapter 5.

Can this positive effect of prior adopters on potential adopters be interpreted as evidence of some kind of knowledge spillover or information sharing between them? Ideally, if we know all the exogenous influences that affect a potential adopter's decision, then we would be able to infer the positive effect of prior adopters as capturing their own effects only. However, there are potential alternative hypotheses that the presence of prior adopters is positively correlated with the technology-adoption decision of potential adopters, even if there are no knowledge spillovers of any kind. We will now look at these alternative hypotheses.

The first alternative hypothesis is that the results are driven by unobserved local-area characteristics that are correlated with both the presence of technology adopters and the decision of potential adopters. Specifically, regions where there are agglomerations of economic activities would provide advantages that are favourable not only to do business but also to adopt new technologies. These things include such obvious factors as the presence of abundant skilled labour (i.e., scientists and engineers who would make the adoption and implementation of technology easier), the local presence of input suppliers and output consumers, the presence of universities or research institutions, tax policies and a good infrastructure. Furthermore, plants in the same region face the same exogenous local influences such as a local research-and-development (R&D) subsidy, tax incentives, or a business cycle that would affect any technology adoption. These location-specific characteristics would idiosyncratically affect the technology-adoption decision of all plants in that region, and some of these effects are positively correlated with the existing number of technology-user plants in the area. Therefore, distinguishing the effects of location-specific characteristics from the effects of the presence of prior adopters is imperative.

The second hypothesis is that the results are driven by unobserved effects operating at various levels that are correlated with both the presence of technology adopters and the decision of potential adopters in a region. Such unobserved effects may operate at the industry level, the technology level, or even at the interaction of industry × region, industry × technology or region × technology levels. For example, the adoption rate of any advanced manufacturing technologies in the Aircraft and aircraft parts industry, Standard Industrial Classification (SIC) 321, is 28% while it is only 4% in the Rubber hose and belting industry, SIC 152. Because of these kinds of industry-level fixed effects, a regional concentration of technology-intensive industries would be positively correlated with the number of technology users in the region. Another example of such unobserved effects would be a cost reduction in the adoption of, say, computer-aided design and engineering (CAD/CAE) that would increase the adoption rate of that technology. Similarly, a local tax incentive or R&D subsidy to a particular industry would increase the overall technology adoption for that industry within the region. Since there are many potential factors that may influence technology adoption at the plant level, it is essential to control for these unobserved effects that operate at various levels.

The third hypothesis is that results are driven by 'omitted' plant characteristics that influence the technology adoption decision. A theory on the differential capacity of firms to absorb, and make good use of, new technical information emphasizes differences in internal expertise, access to financial resources and organizational routines. These differences affect each firm's expected profitability—the incremental returns to investing in the new technology—that, in turn, gives rise to the observed uneven pattern of adoption (Cohen and Levinthal 1990, Dosi 1988, Malerba 1992, Nelson and Winter 1982). Also, plant learning—and ability to act on that information—will also vary by the level of organizational resources, scale of the production process, appropriateness of the new technology to that plant's core-production process and sources of information, all of which may have nothing to do with geography itself. For example, large plants or multi-product plants may well be run by more innovative entrepreneurs who tend to adopt more technologies. Therefore, there may be a plant-specific component to the error term in the specification that is correlated with included right-hand side variables. In addition, there is a possibility that some of the variables are potentially endogenous—for example, a plant introduces a new technology and then decides to locate to a region, or it relocates to a region for the purpose of adopting technologies.

In order to separately identify and estimate the effect of prior adopters on potential adopters from the above-mentioned unobserved effects and thus eliminate them as potential explanations of the results, the following methods are employed. First, the concern that omitted location variables may drive the results is addressed as follows. If the results hold up after inclusion of location-fixed effects, they cannot be driven by any effects that are common at the regional level, such as the presence of universities, location advantage, transportation, tax policies or regional influences. Therefore, we include location-fixed effects at the economic region level—at which both the dependent variable and the key variables are measured.[7] Furthermore, to make sure that the results are not capturing the agglomeration effects—such as the local presence of specialized, skilled labour, input suppliers, output consumers and the overall size of regional manufacturing activities at a finer geographical level than the economic-region level—variables capturing these effects at the census-division level are included. Consequently, these will make sure that the

7. More discussions of the unit of geography are in Section 4.

results are not driven by the agglomeration effects operating at the census-division level as well as any unobserved effects at the economic-region level.

Second, the concern about unobserved effects operating at various other levels is dealt with in the following ways. Industry-, technology- and time-fixed effects are included to control for the effects that are common to the industry, the technology and time. In addition, two variables measuring the average adoption rate of overall technologies by industry × region and the average adoption rate in a region by particular technology × industry are included in the specifications to further control for effects that operate at the industry × region and technology × region levels.[8]

Third, the issue about the unobserved plant heterogeneity is handled by including an extensive set of plant characteristics, such as size, plant status, the number of commodities, ownership and age. Although plant-level heterogeneity would most ideally be controlled by plant-fixed effects, the small variation across the adoption pattern of 22 technologies within a plant does not allow the inclusion of plant-fixed effects. Therefore, variables capturing important plant-level heterogeneity that affects adoption decisions are used instead. The set of plant characteristics included here is the richest plant-level information used in the literature, in the author's opinion.

In addition to the extensive controls and fixed effects mentioned above, the effects of prior adopters are estimated separately, based on the functional, geographical and technological distance from the potential adopter. These separate estimations not only reveal how the effects are bound by the three dimensions, but also serve as a test to show that the results are not driven by any of the alternative hypotheses mentioned above. The reasons for this are as follows. First, the estimation of the effects of prior adopters of the same region, separately by the functional distance from the potential adopter, allows us to determine whether the results are driven by region × technology-fixed effects or if the effects are function/industry specific within each region × technology level. Second, the estimation of the effects of prior adopters of the same technology, separately by the geographic distance, allows us to discern whether the effects are driven by industry × technology-fixed effects or if they are geography specific within each industry × technology level. Finally, the estimation of the effects of prior adopters of the same region, by the technological distance from the potential adopter, allows us to analyse whether the effects are driven by the industry × region-fixed effects or if they are technology specific within each industry × region level. These separate estimations of the effects of prior adopters on potential adopters by the functional, geographical and technological distances confirm that the effects of prior adopters are not driven by any of the potential alternative effects mentioned above, but are very likely capturing the effects of the presence of prior adopters. The only remaining possibility of the spurious result is that the results are driven by fixed effects that operate at the level of region × industry × technology × time. Not only is it very unlikely to come up with fixed effects that operate at this detailed level, but the fact that the results are strongest when prior adopters are in a similar-but-not-the-same industry as the potential adopter provides very compelling evidence of the validity of the results obtained here.

8. The inclusion of fixed effects at the interaction levels would completely capture all the effects. However, due to the variability of the sample, it is not allowed in this specification.

The estimating equation for plant *p*'s adoption of technology $\tau$ at time *t* hence is

$$\begin{aligned}\Pr(ADOPTION_{p\tau irt}) = F(\alpha_0 &+ \beta_1 PriorAdopter\_Similar_{\tau iR,t-1} + \beta_2 PriorAdopter\_Mod.Similar_{\tau iR,t-1} \\ &+\beta_3 PriorAdopter\_Different_{\tau iR,t-1} + \beta_4 RegionalEmployment_{ir,t-1} \\ &+\beta_5 ENGINEER_{r,t-1} + \beta_6 INPUT_{ir,t-1} + \beta_7 OUTPUT_{ir,t-1} \\ &+\beta_8 X_{p,t-1} + \beta_9 Avg\_Ind\_Region_{iR,t-1} + \beta_{10} Avg\_Ind\_Tech_{i\tau,t-1} \\ &+\delta_R + \gamma_i + \varphi_\tau + \lambda_t + \varepsilon_{p\tau irt})\end{aligned}$$

where *F* represents the logistic cumulative distribution. Logit model is used to capture the 'fat tail' of the distribution (i.e., there is a larger proportion of non-adopters of any technology at time *t*). $X_{pirt}$ is a vector of plant characteristics, $Avg\_Ind\_Region_{iRt}$ is an average adoption rate of advanced technologies overall among plants in industry *i* in economic region *R* at time *t*, and $Avg\_Ind\_Tech_{i\tau t}$ is an average adoption rate of technology $\tau$ in industry *i* across economic regions at time *t*. $\delta_R$ is the location fixed effect, $\gamma_i$ is the industry fixed effect, $\varphi_\tau$ is the technology fixed effect, and $\lambda_t$ is the time fixed effect. The variables in the estimating equation are explained in detail in the next chapter and Table 3.

# 4. Data

## 4.1 Sources

The data for the analysis come from numerous sources. The main source is the 1993 Survey of Innovation and Advanced Technology (SIAT). This is a unique, confidential and proprietary data set that surveyed approximately 2,500 plants covering the entire manufacturing sector across Canada. SIAT collected information on various aspects of innovation and adoption of advanced-manufacturing technologies. Specifically, this survey reported information on each plant's adoption of 22 advanced-manufacturing technologies within 6 different technology groups. The technologies are 'general-purpose technologies,' in that they are not specific to any particular industry, but can be used in the production process of any industry.[9] These technologies are listed in Table 1, along with the incidence of use in 1993 and 1984.

**Table 1**
**List of advanced manufacturing technologies and incidence of technology use by plants**

| Advanced manufacturing technologies | 1993 | 1984 |
|---|---|---|
| **Design and engineering** | | |
| Computer-aided design (CAD) and/or computer-aided engineering (CAE) | 27.1 | 1.3 |
| CAD output used to control manufacturing machines (CAD/CAM) | 12.9 | 0.6 |
| Digital representation of CAD output used in procurement activities | 6.0 | 0.2 |
| **Fabrication and assembly** | | |
| Flexible manufacturing cell (FMC) or systems (FMS) | 6.8 | 0.2 |
| Numerically controlled and computer numerically controlled (NC/CNC) machines | 15.0 | 2.8 |
| Materials working laser | 2.4 | 0.0 |
| Pick and place robots | 3.5 | 0.3 |
| Other robots | 3.0 | 0.0 |
| **Automated material handling** | | |
| Automated storage and retrieval system (AS/RS) | 3.0 | 0.2 |
| Automated guided vehicle systems (AGVS) | 1.1 | 0.0 |
| **Inspection and communications** | | |
| Automated sensor-based equipment used for inspection/testing of incoming or in-process materials | 6.1 | 1.0 |
| Automated sensor-based equipment used for inspection/testing of final product | 6.8 | 1.4 |
| Local area network for technical data | 10.5 | 0.4 |
| Local area network for factory use | 8.1 | 1.0 |
| Inter-company computer network linking plant to subcontractors, suppliers and/or customers | 7.5 | 0.1 |
| Programmable controller | 17.1 | 1.9 |
| Computer used for control on the factory floor | 15.6 | 1.5 |
| **Manufacturing information systems** | | |
| Materials requirement planning (MRP) | 15.7 | 1.3 |
| Manufacturing resource planning (MRP II) | 8.5 | 0.2 |
| **Integration and control** | | |
| Computer integrated manufacturing (CIM) | 6.1 | 0.5 |
| Supervisory control and data acquisition (SCADA) | 7.5 | 1.0 |
| Artificial intelligence and/or expert systems | 1.5 | 0.0 |

Note: This table shows results of the author's calculations.
Sources: Statistics Canada, 1993 Survey of Innovation and Advanced Technology and Annual Survey of Manufactures.

9. The concept of General Purpose Technology (GPT) used here is not as broad as the one used in Bresnahan and Trajtenberg (1995).

**Table 2**
**Descriptive statistics of variables**

| | 1984 | 1987 | 1990 |
|---|---|---|---|
| | Mean | | |
| **Plant characteristics** | | | |
| Employment of plant | 61.0 | 76.7 | 88.7 |
| Number of SIC-4[1] industries in which firm operates | 1.98 | 2.20 | 2.85 |
| Number of commodities produced | 2.41 | 1.93 | 2.83 |
| Percentage of multi-plant firms | 0.16 | 0.19 | 0.22 |
| Percentage of foreign-owned plants | 0.14 | 0.17 | 0.20 |
| **Technology spillovers** | | | |
| Number of prior adopters in similar industries | 3.27 | 6.23 | 21.8 |
| Number of prior adopters in moderately similar industries | 1.19 | 6.90 | 16.0 |
| Number of prior adopters in different industries | 14.2 | 54.3 | 127.0 |
| **Employment** | | | |
| Employment in census division ('000) | 72.8 | 73.5 | 73.2 |
| Employment at small plants in census division ('000) | 9.4 | 7.9 | 8.8 |
| Employment at large plants in census division ('000) | 42.5 | 45.8 | 45.6 |
| **Other agglomeration economies** | | | |
| Value of output in upstream industry in census division | 25.5 | 36.6 | 40.5 |
| Value of output in downstream industry in census division | 26.1 | 35.6 | 39.9 |
| Percentage of scientists and engineers in census division | 4.4 | 4.1 | 4.1 |

1. 4-digit Standard Industrial Classification code.
Note: Variables are weighed by 'establishment weight' provided in the 1993 Survey of Innovation and Advanced Technology. This table shows results of the author's calculations.
Sources: Statistics Canada, 1993 Survey of Innovation and Advanced Technology and Annual Survey of Manufactures.

A critical piece of information provided in SIAT is each plant's time of adoption of each of the 22 technologies. This information permits the construction of panel data from the given cross-sectional data set. As a result, a panel-data set consisting of three periods—1984 to 1986, 1987 to 1989 and 1990 to 1992—is constructed. Use of time intervals, rather than use of each year, reduces the effects of recall bias caused by the retrospective nature of panel data, in addition to leaving plenty of regional variations in each period.[10]

Additional information on plant characteristics is obtained from the Annual Survey of Manufactures (ASM). The ASM is a longitudinal database of Canadian manufacturing plants that annually collects information for almost all manufacturing plants. Some 1,902 plants out of the 2,500 plants surveyed in the SIAT are also surveyed in the ASM. Detailed information on plants—such as geographical location, employment, outputs, country of ownership, plant age and multi-plant status—are taken from the ASM for these 1,902 plants.

10. Plants may round the number of years a given technology has been in use. For example, plants may report 5 years instead of 4 or 6 years, and 10 years instead of 9 or 11 years. Indeed, there are peaks at 5 and 10 years, and a lower number of new technology adoptions are reported for 4, 6, 9 and 11 years.

**Table 3**
**Variable names and definitions**

| Variable name | Definition |
|---|---|
| **Technology-spillover variables** | |
| Prior adopters in similar industries | Number of prior adopters of technology $\tau$ in similar industries $i$ in economic region $R$ at time $t$-1 |
| Prior adopters in own SIC-4[1] | number of prior adopters of technology $\tau$ in own SIC-4 industry $i$ in economic region $R$ at time $t$-1 |
| Prior adopters in similar industries excluding own SIC-4 | Number of prior adopters of technology $\tau$ in similar industries excluding own SIC-4 industry $i$ in economic region $R$ at time $t$-1 |
| Prior adopters in moderately similar industries | Number of prior adopters of technology $\tau$ in moderately similar industries $i$ in economic region $R$ at time $t$-1 |
| Prior adopters in different industries | Number of prior adopters of technology $\tau$ in different industries $i$ in economic region $R$ at time $t$-1 |
| **Employment variables** | |
| Regional employment | Employment in census division $r$ at time $t$-1 |
| Employment in similar industries | Employment in similar industries $i$ in census division $r$ at time $t$-1 |
| Employment in own SIC-4 | Employment in own SIC-4 industry $i$ in census division $r$ at time $t$-1 |
| Employment in similar industry excluding own SIC-4 | Employment in similar industries excluding own SIC-4 industry $i$ in census division $r$ at time $t$-1 |
| Employment in moderately similar industries | Employment in moderately similar industries $i$ in census division $r$ at time $t$-1 |
| Employment in different industries | Employment in different industries $i$ in census division $r$ at time $t$-1 |
| **Other agglomeration variables** | |
| Input | Output of upstream suppliers of industry $i$ in region $r$ at time $t$-1 |
| Output | Output of downstream consumers of industry $i$ in region $r$ at time $t$-1 |
| Engineer | Share of scientists and engineers in population in region $r$ at time $t$-1 |
| **Other controls** | |
| Adoption of technologies in an economic region | Mean adoption rate of overall technologies in industry $i$ in economic region $R$ |
| Adoption of a technology in all economic regions | Mean adoption rate of technology $\tau$ in industry $i$ across economic regions |

1. 4-digit Standard Industrial Classification code.
Notes: These variables are used to indicate potential channels of agglomeration externalities.
Sources: Statistics Canada, 1993 Survey of Innovation and Advanced Technology and Annual Survey of Manufactures.

To measure the characteristics of the regional economies, both the ASM and the Census of Population are used. All variables characterizing local manufacturing activities are calculated at the census-division level as to where a plant is located, utilizing information from the ASM. Variables characterizing regional demography are also calculated at the census-division level, using information from the Census of Population.[11]

Other supplementary data come from the National Input–Output Tables from 1983 to 1992. We use the National Input–Output Tables at the most detailed level available, *w*, which consists of 145 3- and 4-digit Standard Industrial Classification (SIC) industries. The tables record the value of intermediate inputs and outputs each industry buys and sells to other industries. Based on this information, forward and backward linkages are calculated.

11. The Census of Population is quinquennial. For each Census, 20% of households receive the 'long questionnaire,' which seeks detailed information on individuals.

The units of geography employed in this paper are economic regions and census divisions. Province, economic region and census division are geographical units, in descending order of size. An economic region is a statistically categorized region, comprising one or more census divisions, but confined within a province or territory.[12,13]

## 4.2 Construction of variables

*Measurement of similarities across industries in terms of pattern of input purchases*

The extent of knowledge spillovers from local prior adopters of technology $\tau$ to potential adopters may depend on the 'relatedness' between the two industries. One of the common criticisms of earlier geographic studies in the use of highly aggregated industry units (typically a 2-digit SIC scheme) to empirically define 'related' industries is that 2-digit SIC may not be appropriate to capture the similarities of industries.[14] For instance, SIC 39 includes Broom, brush and mop industry (in SIC 399) and Jewellery and silverware industry (in SIC 392), which are highly dissimilar in nature.

In the context of studying the effects of knowledge spillovers on technology adoption, the relatedness across industries can be better measured by the similarities in input purchases, which would mimic the similarities in input processes more closely than by standard industry classification. In order to measure the similarities in input purchases, we utilize information on the patterns of input purchases from the National Input–Output Tables at 145 3- and 4-digit SIC industries. For each industry $i$, we calculate its correlation $\rho_{ij}$ with every other industry $j$ in terms of input purchases and then categorize each and every industry into one of three groups, based on the correlation. Industries with a correlation equal or greater than 0.50 are categorized as 'similar' industries, industries with a correlation between 0.50 and 0.20 are categorized as 'moderately similar' industries, and industries with a correlation of less than 0.20 are categorized as 'different' industries.[15] For each industry, the groups of similar, moderately similar and different industries are neither symmetric nor of equal size.[16] Descriptive statistics on the industry categories based on input purchases are compared with the 2-digit SIC industry categories in Table B.1 in Appendix B.

12. In 1991, there were 10 provinces and 2 territories in Canada, with each province and territory being divided into a number of economic regions. There were 68 economic regions, each divided into one or more census divisions. There were 290 census divisions across provinces and territories.
13. While boundaries of census divisions tend to stay constant over the years, there was a major reconstruction of census divisions in the provinces of Quebec and British Columbia in the late 1980s. In order to consistently measure the effects of regional economies, it is important to have a constant geographic region so that regional variables reflect the economic changes within the region, and not the changes due to the sizing of geographical unit. Thus, a constant census division code based on 1976 has been assigned to all plants in all years using Map Info by matching postal codes.
14. For example, Rosenthal and Strange (2001).
15. The benchmark for this grouping choice is based on the distribution of correlations. The distribution of correlations exhibits an asymmetric weak tri-modal pattern: a small percentage of industries in the high range of correlations; a second group concentrated between 0.20 and 0.50; and the remainder in the lower end of the distribution.
16. The average size of each group of industries, in terms of the number of 3-digit SIC industries it contains, is presented in Appendix B, Table B.1, and is compared with the size of 2-digit SIC industries.

*Technology users*

For each technology $\tau$, $T_{\tau iRt}$ is the number of plants in industry $i$ in region $R$ that have already adopted technology $\tau$ as of period $t$.

$$T_{\tau iRt} = \sum_{p \in i,R} (w_p * I^{\tau}_{p\tau iRt})$$

where $I^{\tau}_{p\tau iRt} = \begin{cases} 1 \text{ if plant } p \text{ in industry } i \text{ in region } R \text{ already adopted technology } \tau \text{ prior to time } t \\ 0 \text{ otherwise} \end{cases}$

$w$ is a plant weight that is provided in the survey to make the sample representative of the population. The unit of geography used in the calculation of the number of technology users is the economic region. Since information on technology adopters is drawn from SIAT, it is important to have enough observations in each cell to keep them representative of the population. Therefore, the number of technology adopters is calculated at the level of the economic region, denoted as *R,* rather than at the finer level of the census division, denoted as *r.*

The number of plants in similar industries in the same economic region that have already adopted technology $\tau$ as of time $t$, is calculated simply as

$$PriorAdopter\_Similar_{\tau iRt} = \ln \sum_{j \in F} T_{\tau jRt}$$

where $i$ and $j$ indexes industry, and $F$ represents a group of industries that are categorized as similar industries for each industry $i$. The number of plants in the moderately similar industries and in the different industries which have adopted technology $\tau$ by time $t$, $PriorAdopter\_Mod.Similar_{\tau iRt}$ and $PriorAdopter\_Different_{\tau iRt}$, are calculated likewise, respectively.

Appendix A provides further details about the construction of other variables.

# 5. Results

## 5.1 Main results: The functional scope of technology spillovers

This section presents the main results on how a plant's probability of adopting technology $\tau$ is affected by the local presence of adopters of the same technology, after controlling for various effects. In particular, the main specification estimates how a plant's technology adoption is differently affected by existing technology users depending on its functional similarity to them, where functional similarity is proxied by similarities in the pattern of input purchases. The key variables of interest are therefore prior adopters of the same technology in the same geographical region that operate in similar industries, $PriorAdopter\_Similar_{\tau iRt}$, moderately similar industries, $PriorAdopter\_Mod.Similar_{\tau iRt}$, and different industries, $PriorAdopter\_Different_{\tau iRt}$. Since each plant's decision to adopt technology $\tau$ at time $t$ is conditional on various controls, the regional agglomeration externalities, plant characteristics and fixed effects at industry, region, time and technology levels are included. Estimates on these regressors are discussed later in Sections 5.5 and 5.6.

The main results are presented in the "Similarity in input" column of Table 4. The coefficient on technology adopters in similar industries is estimated to be positive and significant, implying that plants are more likely to adopt a particular technology $\tau$ as the number of prior adopters of the same technology in similar industries in the same region increases. Elasticity of 0.0012 indicates that doubling the number of prior adopters of technology $\tau$ in the similar industries in the same economic region increases a plant's probability of adoption of technology $\tau$ by 0.12%. A plant located in the economic region covering the Greater Toronto Area has a 6% higher probability of adopting the given technology $\tau$ compared with an otherwise identical plant located in a region with 50 times less prior adopters of technology $\tau$ in similar industries, holding everything else constant. The coefficient on technology users in the moderately similar industries is positive and significant with elasticity of 0.00065. This indicates that while the local presence of prior adopters in the moderately similar industries does increase a plant's probability of technology adoption, its effect is only about a half that of the prior adopters in the similar industries. The estimate on technology adopters in different industries reveals that a plant's probability of adoption has a weakly negative correlation with the number of prior adopters in the different industries.

**Table 4**
**Main results, functional scope of technology spillovers**

| Technology spillovers | Similarity in input | | Similarity in output | |
|---|---|---|---|---|
| | Coefficient | Elasticity | Coefficient | Elasticity |
| Prior adopters in similar industries | 0.0388* | 0.0012 | … | … |
| Standard error | (0.0030) | ... | ... | ... |
| Prior adopters in own SIC-4[1] | … | … | 0.0269* | 0.00082 |
| Standard error | … | … | (0.0038) | … |
| Prior adopters in similar industries excluding own SIC-4 | … | … | 0.0402* | 0.0012 |
| Standard error | … | … | (0.0030) | … |
| Prior adopters in moderately similar industries | 0.0214* | 0.00065 | 0.0207* | 0.00063 |
| Standard error | (0.0030) | … | (0.0030) | … |
| Prior adopters in different industries | -0.0187* | -0.00057 | -0.0181* | -0.00055 |
| Standard error | (0.0043) | … | (0.0043) | … |
| Observations | 106,188 | | 106,188 | |
| Log likelihood | 68,172 | | 68,328 | |

… not applicable
* $\chi^2$ statistically significant at $p < 0.05$
1. 4-digit Standard Industrial Classification code.

Notes: Dependent variable: $ADOPTION_{p\tau irt}$. Also included are plant characteristics and agglomeration effects, control variables and fixed effects. Variables are defined in Table 3. This table shows results of the author's calculations.
Sources: Statistics Canada, 1993 Survey of Innovation and Advanced Technology and Annual Survey of Manufactures.

It is noteworthy that the spillover effects of prior adopters of technology exhibit a clear decaying pattern when the functional similarities between prior and potential adopters decrease. The results reveal that plants benefit from the local presence of technology adopters only when those prior adopters are similar enough to themselves in terms of the pattern of input purchases whose processes are similar. This suggests that technology spillovers from prior adopters of technology are confined to functional similarities, and the mere presence of prior adopters of the same technology in the same geographic region does not necessarily provide the benefit of technology spillovers.

An alternative hypothesis can be put forward to explain the significant effect of prior adopters in similar industries; that is, the effect is driven by some exogenous effects that are common to plants in the same industry and located in the same geographical region, namely at technology × industry × region × time level. To eliminate this hypothesis, we further decompose technology adopters in similar industries into two groups: adopters in the same product market as defined by own 4-digit Standard Industrial Classification (SIC) industry and adopters in other industries within similar industries (excluding own 4-digit SIC industry from the similar industry group). Note that since the similar industry group is constructed based on 3- and 4-digit SIC, the 4-digit SIC industry is, by construction, a subset of the similar industries. Because the effect of technology adopters in other industries within the similar industry group is free from a possibility of such spurious correlation at technology × industry × region × time level, a positive effect of them is sufficient to allow us to eliminate the alternative hypothesis of a spurious result arising from fixed effects at the technology × industry × region × time level.

The "Similarity in output" column in Table 4 reports the estimates of this product-market decomposition specification. The results show that the effect of technology adopters in other industries within the similar industry group is positive and significant, which assures us that the effects of prior adopters of technology are not driven by spurious effects that are common to the same industries. This positive and significant effect of the local presence of technology users in other industries within the similar-industry group—even after controlling for fixed effects at the industry, region, time and technology levels, as well as other agglomeration effects at industry × region level—is strongly suggestive of the presence of some kind of communication, namely learning-based knowledge spillovers, across plants adopting the same technology within the same region.

It is interesting to note that the effect of technology adopters in other industries within the similar-industry group is not only positive and significant, but is actually greater than the effect of technology adopters in the same industry. The weaker effect of technology adopters in the same (own 4-digit SIC) industry may be due to 'hampered knowledge spillovers' resulting from plants' incentives to keep information from competitors that are operating in the same product market. If this is the case, then the greatest communication would be more likely to occur among plants operating in different product markets. However, while the stronger effect of adopters in other industries within the similar-industry group is consistent with this explanation, the lack of detailed information in the data does not allow us to identify the underlying forces that drive the results.

## *5.2 Econometric issues*

*Identification issues*

One of the most critical issues in measuring knowledge spillovers from prior adopters to potential adopters lies in how effectively unobserved effects at various levels can be controlled. Since the effects of prior adopters are measured at the technology × industry × region × time level, it is feasible to control for unobserved effects at each individual level to make sure that they do not lead to a spurious result. The "Industry, location fixed effects" column of Table 5 reports the results where time-, technology-, industry-, and region-fixed effects are included. The estimates of technology adopters reported in this column are from a specification where unobservable effects at each of the individual levels are fully captured, using fixed effects.

**Table 5**
**Technology spillovers with various controls**

| | Industry, location fixed effects | | (Industry × Region) controls | | Main regression | |
|---|---|---|---|---|---|---|
| | Coefficient | Elasticity | Coefficient | Elasticity | Coefficient | Elasticity |
| **Technology spillovers** | | | | | | |
| Prior adopters in similar industry | 0.0484* | 0.0015 | 0.0448* | 0.0014 | 0.0388* | 0.0012 |
| Standard error | (0.0029) | ... | (0.0029) | … | (0.0030) | … |
| Prior adopters in moderately similar industry | 0.0240* | 0.00073 | 0.0249* | 0.00076 | 0.0214* | 0.00065 |
| Standard error | (0.0029) | … | (0.0029) | … | (0.0030) | … |
| Prior adopters in different industry | -0.0208* | -0.00064 | -0.0198* | -0.00060 | -0.0187* | -0.00055 |
| Standard error | (0.0043) | … | (0.0043) | … | (0.0043) | … |
| **Fixed effects** | | | | | | |
| Time ( $t$ ) | yes | no | yes | no | yes | no |
| Technology ( $\tau$ ) | yes | no | yes | no | yes | no |
| Industry (SIC-3[1] : $i$ ) | yes | no | yes | no | yes | no |
| Region (economic region: $R$ ) | yes | no | yes | no | yes | no |
| **Other control variables** | | | | | | |
| Adoption of technologies in an economic region | no | no | yes | no | yes | no |
| Adoption of a technology in all economic regions | no | no | no | no | yes | no |
| Observations | 106,188 | | 106,188 | | 106,188 | |
| Log likelihood | 67,163 | | 67,537 | | 67,936 | |

… not applicable
* $\chi^2$ statistically significant at $p < 0.05$

Notes: Dependent variable: $ADOPTION_{p\tau irt}$. Also included are plant characteristics and agglomeration effects. Variables are defined in Table 3. This table shows results of the author's calculations.
Sources: Statistics Canada, 1993 Survey of Innovation and Advanced Technology and Annual Survey of Manufactures.

The natural experiment that one would like to test further is whether the effects of prior adopters of technology are capturing fixed effects that operate at the interaction of industry × region or industry × technology levels. Industry × region effects are controlled using a variable, *Avg_Ind_Region*. This variable captures the effects that are common to plants in the same industry in the same region, across technologies. An example of such effects is the research and development subsidy in electrical and electronic products industries in the Ottawa–Gatineau region, which would increase the overall investment in these industries in that region but would not increase the adoption rate of a specific technology over and above the other technologies. The "Industry × region controls" column in Table 5 presents the results where *Avg_Ind_Region* is included. The results show that the effects of prior adopters remain virtually the same at the 5% level. This implies that the spillover effects presented in the "Industry, location fixed effects" column are not driven by unobserved effects operating at the industry × region level.

Similarly, unobserved effects at the industry × technology level are controlled by including a variable, *Avg_Ind_Tech,* which controls for effects that are common to plants in the same industry adopting the same technology, across regions. An example of such effects would be that computer-aided design is more likely adopted in the aircraft industry than in the petroleum products industry, regardless of the geographical location. The results are presented in the "Main regression" column in Table 5. All three coefficients on technology adopters in different functional groups remain significant and virtually the same in magnitude, except for a small decline in the prior adopters in the similar industries. The stable coefficients on prior adopters across different controls show that the estimated effects of prior adopters are not sensitive across specifications, but are robust both in terms of significance and magnitudes. This supports the claim that the effects of prior adopters are not driven by the industry × region or the industry × technology fixed effects. The specification in the "Main regression" column, the most extensively controlled specification, is used as a main specification. (This specification is the one presented in Section 5.1.)

As a final check, linear probability models with a more extensive set of fixed effects are estimated. While a linear probability model is not appropriate for examining a binary dependent variable, it does allow the inclusion of all fixed effects needed to test for alternative hypotheses. Consequently, the industry × region and the industry × technology fixed effects are included, instead of *Avg_Ind_Region* and *Avg_Ind_Tech,* to fully control for the fixed effects at these levels. The results are presented in Table B.2 in Appendix B. These results provide a consistent story that the estimates of prior adopters tend to stay the same and are robust to the inclusion of additional fixed effects.[17] This strongly confirms that the effects of prior adopters cannot be traced back to a spurious correlation operating at other levels, nor are they driven by the lack of controls and fixed effects.

*Sample selection issues*

Due to the way the data set employed in this paper is constructed, it warrants a discussion of potential sample selection bias. Because of the retrospective panel nature of the data, which is constructed from a cross-sectional survey, the resulting panel data unavoidably consist of only plants that had survived at least till 1993, but exclude plants that exited prior to 1993. Because technology-user plants are more likely to survive (Baldwin and Gu 2004), the resulting sample consequently consists of plants that are more likely to adopt technologies, *ex ante*.

While it is not feasible to obtain a sample that is representative of the population and free from sample selection bias, an alternative method can be used to test if the results are driven by sample selection bias. Intuitively, plants are more likely to survive for a three-year period than for a ten-year period. Consequently, among the three sub-samples with different time periods—1984 to 1986, 1987 to 1989 and 1990 to 1992—the sample of the latest period is expected to suffer least from the sample selection bias and thus be more representative of the population. In order to determine if sample selection bias is present, and is significant enough to affect the results, the estimates from the full sample are compared with the estimates from the sample of the latest period as a benchmark. The "Full sample" and "1990 to 1992" columns of Table 6 report the estimates from the full sample and the latest-period sample, respectively. The results show that the estimates from the full sample and the latest-period sample are similar in terms of the sign, significance and the order of magnitudes for all of the three coefficients on technology adopters. The results provide the consistent story that the effects of the prior adopters are greatest with the functional proximity and monotonically decrease with the dissimilarities. Furthermore, the effects of the prior adopters in the similar industries are estimated to be a little greater in the latest-sample period than in the full-sample period. This suggests that either there is a systematic break between the latest period and the earlier period in the effects of prior adopters, or the estimates in the full sample are downward biased compared with the supposedly less biased

17. While the linear probability model can provide a meaningful comparison, the interpretation of coefficients is inappropriate.

latest sample. Because the estimates from the supposedly less biased sample provide an even stronger support of the results, we would not be concerned that the results are driven by a sample selection bias.

*Endogeneity issues*

One of the critical issues in network literature is the endogeneity problem. In this particular case, the location decision made by plants may be endogenous of their technology adoption decisions. One of the assumptions that are used in this paper is that plants are heterogeneous in their adoptive behaviour. Therefore, it is possible that plants that are more likely a priori to adopt technologies may also be more likely to seek out agglomerations as places to locate. If it is the case that plants that are more likely to adopt technologies move to places first and then later adopt technologies, then the results will overstate the effect of pure information spillovers. Although the existing information does not allow us to separately identify these two effects, it can be tested whether this potential endogeneity issue could be problematic in this case.

**Table 6**
**Sample selection issues**

| | **Full sample** | **1990 to 1992** |
|---|---|---|
| | Coefficient | Coefficient |
| **Technology-spillover variables** | | |
| Prior adopters in similar industries | 0.0355* | 0.0492* |
| Standard error | (0.0030) | (0.0043) |
| Prior adopters in moderately similar industries | 0.0249* | 0.0281* |
| Standard error | (0.0030) | (0.0042) |
| Prior adopters in different industries | -0.0182* | -0.0764* |
| Standard error | (0.0043) | (0.0076) |
| **Other agglomeration effects** | | |
| Regional employment | 0.0656* | -0.010 |
| Standard error | (0.0087) | (0.0123) |
| Input | 0.0760* | 0.161* |
| Standard error | (0.0079) | (0.011) |
| Output | -0.139* | -0.168* |
| Standard error | (0.0088) | (0.012) |
| Engineer | 4.39* | 1.12 |
| Standard error | (0.97) | (1.59) |
| Observations | 106,188 | 39,960 |
| Log likelihood | 67,936 | 35,922 |

* $\chi^2$ statistically significant at $p < 0.05$

Notes: Dependent variable: $ADOPTION_{p\tau irt}$. Also included are plant characteristics and agglomeration effects. Variables are defined in Table 3. This table shows results of the author's calculations.
Sources: Statistics Canada, 1993 Survey of Innovation and Advanced Technology and Annual Survey of Manufactures.

In order to determine how endogenous location decisions are with respect to technology adoption decisions, the timings of location and adoption decisions are examined. The data show that for the majority of plants, the location decision was made well in advance of the technology-adoption decision. The data statistics reveal that the average age of technology-adopting plants (in a new location) is 11.6 years, and the average time of technology use is 3.4 years. Although it is possible that plants move to a region anticipating their future adoption decisions, assuming that plants do not have perfect foresight, it is not very likely that plants made the location decisions on average 8.2 years ahead of their adoption decisions. Furthermore, the average age in a new location is not statistically different between technology-adopting plants and non-adopting plants, where average for non-adopting plants is 10.6 years. These two facts suggest that the endogeneity issue in the location decision would not be material, even if it were to exist.

### *5.3 The geographical scope of technology spillovers*

It is pertinent to examine how far the spillover effects originating from prior adopters of technology $\tau$ extend in terms of the geographical distance. Rather than focusing only on the effects of the 'local' prior adopters as in the previous section, we extend the analysis to the effects of 'geographically distant' prior adopters.

Table 7 presents the results. It reports how the probability of technology adoption is affected by the presence of prior adopters, depending on the geographical distance from the potential adopter. It looks at prior adopters located within 300 kilometres of the potential adopters; prior adopters located from 300 kilometres to 1,000 kilometres; and prior adopters located beyond 1,000 kilometres. The estimates show that the effect of prior adopters within 300 kilometres is positive and significant, with an elasticity of 0.0013; prior adopters from 300 kilometres to 1,000 kilometres is positive, with an elasticity of only 0.0011; and prior adopters beyond 1,000 kilometres is 0.0004. This reveals that the effects of prior adopters of technology are strongest with geographical proximity and they decrease with distance. The closer the geographical distance between the prior and the potential adopter, the greater will be the technology spillovers from prior adopters. This provides evidence of the localization of knowledge spillovers: that is, technology spillovers from prior adopters of technologies are dependent on geographical proximity and they decay with distance.

**Table 7**
**Geographical scope of technology spillovers**

| | Geographical distance | |
|---|---|---|
| | Coefficient | Elasticity |
| **Prior adopters of the same technology in similar industries located within** | | |
| < 300 kilometres | 0.0425* | 0.0013 |
| Standard error | (0.017) | … |
| 300 kilometres to 1,000 kilometres | 0.0377* | 0.0011 |
| Standard error | (0.0055) | … |
| > 1,000 kilometres | 0.0137* | 0.0004 |
| Standard error | (0.0032) | … |
| **Employment effects** | | |
| Employment in similar industries | -0.0710* | -0.0022 |
| Standard error | (0.0079) | … |
| Employment in moderately similar industries | 0.0625* | 0.0019 |
| Standard error | (0.0039) | … |
| Employment in different industries | -0.0096 | -0.0029 |
| Standard error | (0.0073) | … |
| Observations | 106,188 | |
| Log likelihood | 68,408 | |

… not applicable
* $\chi^2$ statistically significant at $p < 0.05$
Notes: Dependent variable: $ADOPTION_{p\tau irt}$ . Also included are plant characteristics, other agglomeration effects, control variables and fixed effects. Variables are defined in Table 3. This table shows results of the author's calculations.
Sources: Statistics Canada, 1993 Survey of Innovation and Advanced Technology and Annual Survey of Manufactures.

Furthermore, this geographically decaying pattern of the effects of prior adopters also serves as another alternative test of spurious correlation arising at the technology × industry level. If the estimates are driven by technology × industry fixed effects, the result would show that the effects are not differentiated accordingly to the geographic distance. The decaying effects of prior adopters depending on the geographical distance show that the effects of prior adopters are geographic specific within the technology × industry level.

## *5.4 The technological scope of technology spillovers*

Are spillover effects of one particular technology confined to the same technology or spread over other technologies as well? To answer this question, we analyse how a plant's probability of adopting technology $\tau$ is affected by the presence of prior adopters of any technologies rather than limited only to the adopters of the same technology $\tau$. This investigation also serves as an identification test. If the spillover effect from prior adopters comes through a technology-specific channel within each industry × region level (i.e., technology × industry × region), then we can successfully eliminate the possibility that the result obtained here is driven by some other effects that operate at the industry × region level.

Table 8 presents the results for three different specifications. The specification for the "Same technology" column assumes that the technology spillovers are exclusively from prior adopters of the same technology, whereas specifications for the "Technology group" and "All technologies" columns allow that technology spillovers can come from prior adopters of any of the 22 technologies. The "Same technology" column reports the benchmark result on the effects of prior adopters of the same technology $\tau$. The "Technology group" column reports the effects of adopters of any technologies in two groups: adopters of the same group of technologies as $\tau$ and adopters of different groups of technologies from $\tau$. The "All technologies" column presents the effects of local adopters of any technologies in three groups: adopters of the same technology, adopters of the same group of technologies (excluding the same technology) and adopters of the different groups of technologies.

The estimating equation for the specification presented in the "All technologies" column of Table 8 is

$$\begin{aligned}\Pr(ADOPTION_{p\tau irt}) = F(&\alpha_0 + \beta_1 Adopter\_SameTech\_Similar_{\tau ir,t-1} + \beta_2 Adopter\_SameGroupT\_Similar_{\tau ir,t-1} \\ &+\beta_3 Adopter\_DiffGroupT\_Similar_{\tau ir,t-1} + \beta_4 Adopter\_SameTech\_Mod.Similar_{\tau ir,t-1} \\ &+\beta_5 Adopter\_SameGroupT\_Mod.Similar_{\tau ir,t-1} + \beta_6 Adopter\_DiffGroupT\_Mod.Simnilar_{\tau ir,t-1} \\ &+\beta_7 Adopter\_SameTech\_Diff_{\tau ir,t-1} + \beta_8 Adopter\_SameGroupT\_Diff_{\tau ir,t-1} \\ &+\beta_9 Adopter\_DiffGroupT\_Diff_{\tau ir,t-1} + \beta_4 RegionalEmployment_{ir,t-1} + \beta_5 ENGINEER_{ir,t-1} \\ &+\beta_6 INPUT_{ir,t-1} + \beta_7 OUTPUT_{ir,t-1} + \beta_8 X_{pir,t-1} + Avg\_Ind\_Region_{ir,t} + Avg\_Ind\_Tech_{i\tau,t} \\ &+\delta_r + \gamma_i + \varphi_\tau + \lambda_t + \varepsilon_{p\tau irt}).\end{aligned}$$

**Table 8**
**Technological scope of spillovers**

| | Same technology | | Technology group | | All technologies | |
|---|---|---|---|---|---|---|
| | Coefficient | Elasticity | Coefficient | Elasticity | Coefficient | Elasticity |
| **Prior adopters in similar industries that have adopted** | | | | | | |
| Technology in same group | … | … | 0.0256* | 0.00077 | … | … |
| Standard error | … | … | (0.0028) | … | … | … |
| Same technology | 0.0355* | 0.0011 | … | … | 0.0478* | 0.0014 |
| Standard error | (0.0030) | … | … | … | (0.0032) | … |
| Other technology in same group | … | … | … | … | -0.0004 | -0.00001 |
| Standard error | … | … | … | … | (0.0030) | … |
| Technology in different group | … | … | -7 E-5* | -2 E-6 | -0.0001* | -3E-6 |
| Standard error | … | … | (0.00002) | … | (0.00002) | … |
| **Prior adopters in moderately similar industries that have adopted** | | | | | | |
| Technology in same group | … | … | 0.0020 | 0.00006 | … | … |
| Standard error | … | … | (0.0029) | … | … | … |
| Same technology | 0.0249* | 0.00076 | … | … | 0.0503* | 0.0015 |
| Standard error | (0.0030) | … | … | … | (0.0032) | … |
| Other technology in same group | … | … | … | … | -0.0194* | -0.0006 |
| Standard error | … | … | … | … | (0.0030) | … |
| Technology in different group | … | … | -0.0002* | -5E-6 | -0.0002* | -6E-6 |
| Standard error | … | … | (0.00002) | … | (0.00003) | … |
| **Prior adopters in different industries that have adopted** | | | | | | |
| Technology in same group | … | … | -0.1020* | -0.003 | … | … |
| Standard error | … | … | (0.0050) | … | … | … |
| Same technology | -0.0182* | -0.00055 | … | … | -0.0023 | -0.00007 |
| Standard error | (0.0043) | … | … | … | (0.0045) | … |
| Other technology in same group | … | … | … | … | -0.0755* | -0.002 |
| Standard error | … | … | … | … | (0.0041) | … |
| Technology in different group | … | … | -0.0002* | -6E-6 | -0.0002* | -6E-6 |
| Standard error | … | … | (7E-06) | … | (7E-06) | … |
| Observations | 106,188 | | 106,188 | | 106,188 | |
| Log likelihood | 67,936 | | 69,069 | | 69,539 | |

… not applicable
* $\chi^2$ statistically significant at $p < 0.05$
Notes: Dependent variable: $ADOPTION_{p\tau irt}$ . Also included are plant characteristics and agglomeration effects, control variables and fixed effects. Variables are defined in Table 3. This table shows results of the author's calculations.
Sources: Statistics Canada, 1993 Survey of Innovation and Advanced Technology and Annual Survey of Manufactures.

Because technology adopters in the similar industries are of the most interest, and have the greatest effect, the effects of prior adopters in the similar industries are discussed here. The first three estimates in the "All technologies" column exhibit a clear pattern, showing that effects of prior adopters decline with the technological distance. A plant's probability of adopting technology $\tau$ increases by 0.014% when the number of adopters of the same technology $\tau$ in the similar industries in the same economic region increases by 1%. However, the change in the probability of adoption due to the prior adopters of the same group of technologies (excluding the same technology $\tau$) is not significant, while the effect of adopters of the different group of technologies is very small and negative with an elasticity of -0.00001. The results indicate that the positive spillover effects of prior adopters are exclusively coming from only those adopters of the same technology. Consequently, this proves that technological proximity is an important aspect in knowledge spillovers from prior adopters to potential adopters. The closer, or the more similar, the technology adopted by prior adopters is to the technology to be adopted by potential adopters, the greater are the spillover effects.

Furthermore, the results reconfirm that the positive effects of the local presence of technology users come through a technology-specific channel within each industry × region level. This is strong evidence that the spillover effects obtained in this paper are not driven by factors that are common to the industry × region or the technology × region levels, but instead are driven by factors that work at the interaction of the technology × industry × region × time level. Incorporating the finding of the main result in Section 5.1, where the spillover effects are greatest from technology users in other industries rather than adopters in own 4-digit SIC industry, the spillover effects identified in this paper are at an even higher level than the technology × industry × region × time level, and hence substantiate the core results once again.

## *5.5 Other agglomeration effects*

Previous sections have analysed how the presence of prior adopters of technology affects potential adopters' decisions in the functional proximity, geographical proximity and technological proximity. However, there are other external factors that affect technology adoption in addition to the knowledge spillovers from prior users. We will discuss the effects of other agglomeration externalities—the size of the regional economic activities, a skilled labour force and the presence of input suppliers and output consumers—that affect the probability of technology adoption. The results are presented in Table 9.

The first column in the upper panel of Table 9 presents how the scale of regional manufacturing activities, measured by regional employment, affects the probability of technology adoption of a plant. The coefficient on regional employment, $EMP\_REGION_{ir,t-1}$, is positive and significant, with elasticity of 0.02. This implies that a plant located in a census division with manufacturing employment of 300,000 has a 20% higher probability of adopting a given technology compared with a plant located in a census division with 10 times less manufacturing employment of 30,000, holding everything else equal. This supports the claim that technology adoption in a region is facilitated by the regional agglomeration.

It is natural to ask what type of regional agglomeration is responsible for facilitating technology adoption in a region. Is it regional specialization in just a few industries (as in Marshall 1920) or regional diversification of industries (as in Jacobs 1970) that facilitates technology adoption? The second column in the top panel of Table 9 presents how the agglomerations of different groups of industries—categorized in terms of the similarities in input purchases—differently affect the probability of technology adoption in a region. The variable, 'employment in similar industries,' captures how a plant's probability of technology adoption is affected by the size of the employment in similar industries. The negative estimated coefficient implies that the probability that a plant adopts a technology actually decreases with the agglomeration of similar industries in a region. The results further reveal that a plant is more likely to adopt a technology as the size of the moderately similar industries in a region increases, but it does not seem to be affected by the size of the different industries in a region.

**Table 9**
**Other agglomeration effects**

| Agglomeration effects | Technology adoption of a plant | | Technology adoption in a region | |
|---|---|---|---|---|
| | Coefficient | Elasticity | Coefficient | Elasticity |
| **Employment effects** | | | | |
| Regional employment | 0.0656* | 0.020 | … | … |
| Standard deviation | (0.0087) | … | … | … |
| Employment in similar industries | … | … | -0.0714* | -0.0022 |
| Standard deviation | … | … | (0.0079) | … |
| Employment in moderately similar industries | … | … | 0.0563* | 0.0017 |
| Standard deviation | … | … | (0.0039) | … |
| Employment in different industries | … | … | 0.0065 | 0.00020 |
| Standard deviation | … | … | (0.0073) | … |
| **Other agglomeration effects** | | | | |
| Input | 0.0760* | 0.014 | 0.0760* | 0.014 |
| Standard deviation | (0.0079) | … | (0.0079) | … |
| Output | -0.139* | -0.013 | -0.139* | -0.013 |
| Standard deviation | (0.0088) | … | (0.0088) | … |
| Engineer | 4.39* | 1.07 | 4.39* | 1.07 |
| Standard deviation | (0.97) | … | (0.97) | … |
| Observations | 106,188 | | 106,188 | |
| Log likelihood | 67,937 | | 68,172 | |

… not applicable
* $\chi^2$ statistically significant at $p < 0.05$

Notes: Dependent variable: $ADOPTION_{p\tau irt}$. Also included are plant characteristics, other agglomeration effects, control variables and fixed effects. Variables are defined in Table 3. This table shows results of the author's calculations.
Sources: Statistics Canada, 1993 Survey of Innovation and Advanced Technology and Annual Survey of Manufactures.

This suggests that the agglomeration of moderately similar industries in a region, not the agglomeration of similar or different industries, is what facilitates technology adoption. This supports Jacobs' (1970) claim of diversification economies: plants benefit more from having a diverse set of industries that brings new ideas and practices to one place. The result, however, points to a more interesting implication: learning is maximized when plants are different enough to learn from, yet they are similar enough that the knowledge learned is relevant. This provides an added insight in terms of how diverse should the diversified economies be in order to optimize inter-organizational learning and to facilitate technology adoption in a region. An alternative interpretation on the negative effect of the agglomeration of the similar industries is that fierce competition for market share may bring down profits and, consequently, decrease the likelihood of technology adoption. Both hypotheses consistently emphasize that not only does the size of the regional agglomeration matter but, more importantly, which agglomeration of industries may be more relevant.

This result is comparable to that obtained on the effect of prior adopters. In the case of technology users, the effects are greatest when prior adopters are in the similar-industry group, yet they should not be in the same industry. However, for employment, the scope is broader in that the effects are greater when regional employment is high in moderately similar industries.

The lower panel of Table 9 presents the effects of the presence of scientists and engineers, input suppliers and output consumers. The coefficient on $ENGINEER_{r,t-1}$ is estimated to be highly significant, with an elasticity of 1.07. This implies that a 1-percentage-point change in the share of scientists and engineers in the population in a census division, say from 4.1% to 5.1% (or, 24% change in the share), increases the probability of a plant adopting a given technology by 26%.[18] The significant effect of a regional specialized, skilled labour force is consistent with the claim that having an abundance of people who have technological knowledge and know-how increases the absorptive capacity, and hence increases the likelihood of the technology adoption in the region.[19] The effects of the 'local presence of input suppliers in a region' are estimated to be positive and significant, supporting the theory that technology adoption is enhanced by the presence of input suppliers in the region.[20] Quantitatively, the elasticity of 0.014 indicates that the magnitude of the effect of the local suppliers is about two thirds of the effect of the regional employment.

## *5.6 Organizational characteristics*

In analysing the effects of knowledge spillovers and other regional agglomeration aspects, it is of great importance to control for plant heterogeneity and not come to false conclusions on the effects of externalities for each plant. Table 10 presents the estimated effects of plant characteristics that are controlled throughout the various specifications presented in this paper. Because estimates of plant characteristics remain very stable and robust throughout specifications, estimates from the main specification are presented and discussed here.

The estimated effect of employment indicates that a plant's probability of technology adoption increases by 0.22% with a 1% increase in plant employment size. This is consistent with the theory that organizational capabilities and resources are one of the most important factors in technology adoption. The negative effect of the number of commodities produced in a plant suggests that the internal economies of scale—which are inversely correlated with the number of commodities—are positively related with technology adoption, even after controlling for plant capacity. This may be due to the spread of the costs of technology over the greater volume of output that is produced when the scale of production becomes larger. Diversity in information channels, as measured by the number of 4-digit SIC industries in which a plant operates, is positively correlated with technology adoption. Furthermore, technology adoption is less likely in single-plant firms or domestically (Canadian) owned plants compared with plants in multi-plant firms or foreign-owned plants, even after controlling for plant size. This suggests that the benefits of being a part of a multi-plant or foreign-owned firm not only come from plant size, but also from the information and resources available from elsewhere.[21]

18. The average share of scientists and engineers in a region is 4.1%, and the variation in a region is fairly small. Since elasticity in the logit model captures the change in probability due to a percentage change of an independent variable at a local point, the interpretation of elasticities in the logit should be done with care. With the S-shaped cumulative distribution function, an increase in the probability diminishes when moving to the higher value of a variable.
19. This finding is consistent with that of Dumais, Ellison and Glaeser (1997) that labour pooling is one of the most significant externalities of agglomeration.
20. The importance of local suppliers is also documented in Kelley and Helper (1996).
21. The higher technology uptake rates among foreign-owned firms are documented in Baldwin and Gu (2004).

**Table 10**
**Organizational characteristics**

| Variable | Main regression | |
|---|---|---|
| | Coefficient | Elasticity |
| Size | 0.557* | 0.017 |
| Standard deviation | (0.0076) | … |
| Age | -0.0752* | -0.0023 |
| Standard deviation | (0.009) | … |
| Diversity | 0.100* | 0.003 |
| Standard deviation | (0.0085) | … |
| Commodity | -0.115* | -0.0035 |
| Standard deviation | (0.0091) | … |
| Small | -0.0407* | … |
| Standard deviation | (0.020) | … |
| Foreign | 0.0860* | … |
| Standard deviation | (0.015) | … |
| Single | -0.182* | … |
| Standard deviation | (0.016) | … |
| Observations | 106,188 | … |
| Log likelihood | 67,936 | … |

… not applicable
* $\chi^2$ statistically significant at $p < 0.05$

Notes: Dependent variable: $ADOPTION_{p\tau irt}$. Also included are prior adopters, other agglomeration effects, control variables and fixed effects; plants are small if employment is less than 20. This table shows results of the author's calculations. *Size* is equal to total employment; *age* is plant age; *diversity* is the number of Standard Industrial Classification 4-digit industries in which a plant operates; *commodity* is the number of commodities a plant produces; *small*: plants are small if employment is less than 20; *foreign* is a dummy variable for a foreign-owned plant; *single* is a dummy variable for single-plant firms. *Small, foreign* and *single* are all equal to 1.
Sources: Statistics Canada, 1993 Survey of Innovation and Advanced Technology and Annual Survey of Manufactures,.

# 6. Conclusion

In this paper we began by documenting the higher degree of geographic concentration among technology adopters than in plants overall. Motivated by this observation, along with frequently mentioned benefits of knowledge spillovers in agglomerated regions, this paper has investigated the presence of knowledge spillovers in technology adoption by analysing the pattern of technology adoption across plants and, if it exists, the scope of the knowledge spillovers. We used various rich sources of information and surveys to carefully identify knowledge spillovers from prior adopters of technology to potential adopters of technology, looking separately at the effects of various other agglomeration externalities—exogenous effects, local amenities and plant heterogeneity. We did this by analysing the scope of knowledge spillovers along the various dimensions of sectoral, geographical and technological proximities.

The key finding of this paper is that a plant's probability of adopting a specific technology is facilitated by the presence of local prior adopters of the same technology in similar industries. By identifying the knowledge spillover effects along the interaction of technology × industry × region × time, this investigation has overcome the difficulties of identifying unobservable-knowledge spillover that may affect technology-adoption decisions. Furthermore, by showing that the greatest spillover effects are from prior adopters in the similar-process-yet-different-product market, it provides a very convincing story that the effects identified are highly unlikely to be a result of spurious correlation at any level. The distinct monotonically decaying pattern of knowledge spillovers in all three dimensions of functional, geographical and technological distance confirms the result. This paper finds that knowledge spillovers from prior adopters are bounded along the three dimensions: geographical proximity, production-process proximity and technological proximity.

# *Appendix A: Construction of variables*

## 1. Variables on other agglomeration externalities

The following measures of agglomeration effects are calculated at the level of the census division, denoted as *r*, in which the plant is located, using the information from the Annual Survey of Manufactures (ASM).[22] Because the ASM comprises almost all manufacturing plants, these agglomeration effects can be measured at the higher level of census division without worrying whether it is representative of the population.

The scale of manufacturing activities in a region, $Regional\ Employment_{rt}$, is measured as the natural log of employment in the manufacturing sector in the census division. Similar to prior adopters of technology, $Regional\ Employment_{rt}$ can be decomposed into three groups: employment in similar, moderately similar and different industries.

Specialized skilled labour in a region, $Engineer_{rt}$, is calculated as the proportion of people with science or engineering degrees in the census division.[23]

$$Engineer_{rt} = \left( \frac{Scientists \,\&\, Engineers_{rt}}{population_{rt}} \right)$$

The presence of input suppliers for industry *i* in census division *r* at time *t* is calculated as

$$Input_{irt} = \ln\left( \sum_{j \neq i} I_{jit} \frac{E_{jrt}}{E_{jt}} \right)$$

where $I_{jit}$ is the value of industry *i*'s input that comes from industry *j* at time *t*, $E_{jrt}$ is industry *j*'s employment in census division *r* at time *t*, and $E_{jt}$ is total employment in industry *j* at time *t*. Since the National Input–Output Tables provide the flows of input and output at the national

22. One could argue that for the labour market measure, it may be more appropriate to use functional urban areas (e.g., metropolitan areas) that take account of commuting patterns rather than use census divisions. Despite this, census divisions are used for the following reason: because a significant portion of plants in the data are located in non-metropolitan areas, the use of functional urban areas would entail the dropping of these observations. Given the size of the data set and the valuable information contained in plants that are located in non-metropolitan areas, it is worthwhile keeping as many observations as possible, even if it means that we have to use census divisions rather than more appropriate functional urban areas.
23. Information on the major field of study is obtained from the Census of Population. This information has been collected since 1986. Hence, for observations for Period 1 (1985 to 1987), the 1986 Census of Population is used. Using labour information from 1986 for Period 1 would not make much difference, since a change in the proportion of people with science or engineering degrees is expected to be very small.

level, values at the regional level are calculated using the proportion of employment in the census division over national employment. The presence of output purchasers for industry *i* in census division *r* at time *t* is calculated similarly as

$$Output_{irt} = \ln\left(\sum_{j \neq i} O_{jit} \frac{E_{jrt}}{E_{jt}}\right)$$

where $O_{jit}$ is the value of industry *i*'s output that goes to industry *j*.

## 2. Organizational characteristics

$X_{pirt}$ is a vector of plant characteristics that includes: Size (plant's employment) to capture the willingness, the ability and the profitability of an organization to adopt new technology;[24] Age (plant age) to capture the differences in a plant's adaptability and flexibility in response to the newly available technologies; Commodity (number of commodities produced in a plant) to capture the extent of technology use and the reduction in the adoption cost arising from the use of processes within a single operating unit to produce or distribute more than one product; Diversity[25] (number of 4-digit SIC industries in which a plant operates) to capture the diversity of an organization's information channel and opportunities to learn about potential knowledge; Foreign (dummy variable for a foreign-owned plant) to capture the advantage of an internal access to the parent firm elsewhere and an access to certain resources and information that are not available to domestically owned plants;[26] and Single (a dummy variable for single-plant firms) to capture the differences between plants that are a part of a multi-plant firm versus single-plant firms in terms of the access to non-local resources, knowledge and information.

24. For more detailed theories on the importance of firm capabilities in technology adoption, see Kelley and Helper (1996), Dosi (1988), Cohen and Levin (1989) and March (1981).
25. For more on this, see Kelley and Helper (1996).
26. Baldwin and Diverty (1995) show that Canadian plants are less productive than foreign-controlled plants.

# Appendix B

## Table B.1
## Summary statistics of sizes of related industries

| Industry category | Average number of SIC-3 industries | Standard deviation | Minimum | Maximum |
|---|---|---|---|---|
| Similar industries | 6.65 | 5.61 | 1 | 20 |
| Moderately similar industries | 8.89 | 4.02 | 0 | 33 |
| Different industries | 92.46 | 9.60 | 69 | 107 |
| SIC-2 industry | 4.95 | 2.61 | 1 | 9 |

Notes: SIC stands for Standard Industrial Classification. This table shows results of the author’s calculations.
Sources: Statistics Canada, 1993 Survey of Innovation and Advanced Technology and Annual Survey of Manufactures.

## Table B.2
## Linear probability models with fixed effects

| | Economic region | Census division | Economic region × SIC-3[1] | Census division × SIC-3 | Technology × SIC-3 |
|---|---|---|---|---|---|
| **Technology use linkage** | | | | | |
| Prior adopters in similar industries | 0.0019* | 0.0018* | 0.0016* | 0.0018* | 0.0015* |
| Standard error | (7.08) | (6.57) | (5.85) | (6.71) | (5.35) |
| Prior adopters in moderately similar industries | 0.0014* | 0.0015* | 0.0015* | 0.0015* | 0.0014* |
| Standard error | (5.21) | (5.42) | (5.63) | (5.51) | (5.38) |
| Prior adopters in different industries | 0.00002 | 0.00003 | 0.0002 | 0.00007 | 0.0003 |
| Standard error | (0.07) | (-0.44) | (0.55) | (0.22) | (0.39) |
| **Fixed effects** | | | | | |
| Time ( $t$ ) | yes | yes | yes | yes | yes |
| Technology ( $\tau$ ) | yes | yes | yes | yes | yes |
| Industry (SIC-3 : $i$ ) | yes | yes | no | no | no |
| Region (economic region: $R$) | yes | no | no | no | no |
| Region (census division: $r$ ) | no | yes | no | no | no |
| Region-industry (SIC-3*economic region : $i \times R$ ) | no | no | yes | no | no |
| Region-industry (SIC-3*cendus division: $i \times r$ ) | no | no | no | yes | no |
| Industry-technology (SIC-3*Technology : $i \times \tau$ ) | no | no | no | no | yes |
| Observations | 105,902 | 105,902 | 105,902 | 105,902 | 105,902 |
| R-square | 0.051 | 0.059 | 0.061 | 0.072 | 0.059 |

* $\chi^2$ statistically significant at $p < 0.05$
1. 3-digit Standard Industrial Classification code.

Notes: Dependent variable: $ADOPTION_{p\tau irt}$. Also included are plant characteristics and agglomeration effects. Variables are defined in Table 3. This table shows results of the author’s calculations.
Sources: Statistics Canada, 1993 Survey of Innovation and Advanced Technology and Annual Survey of Manufactures.

# References


Audretsch, David B., and Maryann P. Feldman. 1996. "R&D spillovers and the geography of innovation and production." *The American Economic Review.* 86, 3: 630–640.

Baldwin, John R., and Brent Diverty. 1995. *Advanced Technology Use in Canadian Manufacturing Establishments.* Analytical Studies Branch Research Paper Series. Catalogue no. 11F0019MIE1995085. Ottawa: Statistics Canada.

Baldwin, John R., and Wulong Gu. 2004. *Innovation, Survival and Performance of Canadian Manufacturing Plants.* Economic Analysis (EA) Research Paper Series. Catalogue no. 11F0027MIE2004022. Ottawa: Statistics Canada.

Badaracco, Joseph L., Jr. 1991. *The Knowledge Link: How Firms Compete Through Strategic Alliances*. Boston, Mass.: Harvard Business School Press.

Bresnahan, Timothy F., and Manuel Trajtenberg. 1995. "General purpose technologies: Engines of growth?" *Journal of Econometrics.* 65, 1: 83–108.

Carlsson, Bo, and Staffan Jacobsson. 1994. "Technological system and economic policy: The diffusion of factory automation in Sweden." *Research Policy*. 23, 3: 235–248.

Case, Anne. 1992. "Neighborhood influence and technological change." *Regional Science and Urban Economics.* 22, 3: 491–508.

Caves, Richard E. 1989. *Multinational Enterprise and Economic Analysis.* Cambridge, U.K.; New York: Cambridge University Press.

Chandler, Alfred D., Jr. 1990. *Scale and Scope: The Dynamics of Industrial Capitalism.* Cambridge, Mass.: Belknap Press of Harvard University Press.

Chinitz, Benjamin. 1961. "Contrasts in agglomeration: New York and Pittsburgh." *American Economic Review.* 51, 2: 279–89.

Cohen, Wesley M., and Richard C. Levin. 1989. "Empirical studies of innovation and market structure." In *Handbook of Industrial Organization*. R.C. Schmalense and R.D. Willig. (eds.). 2, 18: 1059–1101. New York: Elsevier.

Cohen, Wesley M., and Daniel A. Levinthal. 1990. "Absorptive capacity: A new perspective on learning and innovation." *Administrative Science Quarterly.* 35, 1: 128–152.

DiMaggio, Paul J., and Walter W. Powell. 1983. “The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields.” *American Sociological Review.* 48, 2: 147–160.

Dore, Ronald P. 1983. “Goodwill and the spirit of market capitalism.” *British Journal of Sociology.* 34, 4: 459–82.

Dore, Ronald P. 1986. *Flexible Rigidities: Industrial Policy and Structural Adjustment in the Japanese Economy, 1970–80*. Stanford, Cal.: Stanford University Press.

Dosi, Giovanni. 1988. “Sources, procedures, and microeconomic effects of innovation.” *Journal of Economic Literature.* 26, 3: 1120–1171.

Dumais, Guy, Glenn Ellison and Edward L. Glaeser. 1997. *Geographic Concentration as a Dynamic Process*. NBER Working Paper Series no. 6270. Cambridge, Mass.: National Bureau of Economic Research.

Dunning, John H. 1998. “Globalization, technological change, and the spatial organization of economic activity.” In *The Dynamic Firm.* 27–42. A. Chandler Jr., P. Hagström and Ö. Sölvell. (eds.). Oxford: Oxford University Press.

Duranton, Gilles, and Diego Puga. 2004. “Micro-foundations of urban agglomeration economies.” In *Handbook of Regional and Urban Economics.* J.V. Henderson and J.-F. Thisse. (eds.). 4, 48: 2063–2117. Elsevier.

Ellison, Glenn, and Edward L. Glaeser. 1997. “Geographic concentration in U.S. manufacturing industries: A dartboard approach.” *Journal of Political Economy.* 105, 5: 889–927.

Feldman, Maryann P., and David B. Audretsch. 1999. “Innovation in cities: Science-based diversity, specialization and localized competition.” *European Economic Review.* 43, 2: 409–429.

Fujita, Masahisa, Paul R. Krugman and Anthony Venables. 1999. *The Spatial Economy: Cities, Regions, and International Trade.* Cambridge, Mass.: The MIT Press.

Gertler, Meric S. 1995. “‘Being there:’ Proximity, organization, and culture in the development and adoption of advanced manufacturing technologies.” *Economic Geography*. 71, 1: 1–26.

Gertler, Meric S. 2001. “Tacit knowledge and the economic geography of context, or the undefinable tacitness of being (there).” Paper presented at the Nelson and Winter DRUID Summer Conference, Aalborg, Denmark. Toronto: University of Toronto, Centre for International Studies.

Glaeser, Edward L., Hedi D. Kallal, Jose A. Scheinkman and Andrei Shleifer. 1992. “Growth in cities.” *Journal of Political Economy.* 100, 6: 1126–1152.

Globerman, Steven. 1975. "Technological diffusion in the Canadian tool and die industry." *The Review of Economics and Statistics.* 57, 4: 428–434.

Hanson, Gordon H. 2000. *Scale Economies and the Geographic Concentration of Industry*. NBER Working Paper Series no. 8013. Cambridge, Mass.: National Bureau of Economic Research.

Harrison, Bennett. 1994. *Lean and Mean: The Changing Landscape of Corporate Power in the Age of Flexibility*. New York: Basic Books.

Harrison, Bennett, M.R. Kelley and J. Gant. 1996. "Innovative Firm Behavior and Local Milieu: Exploring the Intersection of Agglomeration, Firm Effects, and Technological Change." *Economic Geography.* 72, 3: 233–258.

Harrison, Bennett, Maryellen R. Kelley and Jon Gant. 1996. "Specialization versus diversity in local economies: The implications for innovative private-sector behaviour." *Cityscape: A Journal of Policy Development and Research.* 2, 2: 61–92. Washington, D.C.: U.S. Department of Housing and Urban Development. Office of Policy Development and Research.

Helpman, Elhaman, and Manuel Trajtenberg. 1998. "Diffusion of general purpose technologies." In *General Purpose Technologies and Economic Growth*. 1–13. E. Helpman. (ed.). Cambridge, Mass.: The MIT Press.

Helper, Susan. 1995. *Supplier Relations and Adoption of New Technology: Results of Survey Research in the U.S. Auto Industry*. NBER Working Paper Series no. 5278. Cambridge, Mass.: National Bureau of Economic Research.

Henderson, J. Vernon 1999. *Marshall's Scale Economies*. NBER Working Paper Series no. 7358. Cambridge, Mass.: National Bureau of Economic Research.

Holmes, Thomas J. 2002. *The role of cities: Evidence from the placement of sales offices.* Staff Report no. 298. Minneapolis, Minn.: Federal Reserve Bank of Minneapolis.

Jacobs, Jane. 1970. *The Economy of Cities*. New York: Vintage Books.

Jaffe, Adam B., Manuel Trajtenberg and Rebecca Henderson. 1993. "Geographic localization of knowledge spillovers as evidenced by patent citations." *Quarterly Journal of Economics.* 108, 3: 577–598.

Kelley, Maryellen R. 1993. "Organizational resources and the industrial environment: the importance of firm size and interfirm linkages to the adoption of advanced manufacturing technology." *International Journal of Technology Management.* 8: 33–68.

Kelley, Maryellen R., and S. Helper. 1996. *Firm Size and Capabilities, Regional Agglomeration, and the Adoption of New Technology.* Industrial Performance Centre working paper. Cambridge, Mass.: Massachusetts Institute of Technology.

Krugman, Paul. 1991a. “Increasing returns and economic geography.” *The Journal of Political Economy.* 99, 3: 483–499.

Krugman, Paul. 1991b. *Geography and Trade.* Cambridge, Mass.: The MIT Press.

Landes, David S. 1998. *The Wealth and Poverty of Nations: Why Some Are so Rich and Some so Poor.* New York: W.W. Norton.

Lane, Sarah. 1991. “The determinants of investment in new technology.” *American Economic Review*. 81, 2: 262–265.

Levin, Richard C., Alvin K. Klevorick, Richard R. Nelson and Sydney G. Winter. 1987. *Appropriating the returns from industrial research and development*. Brookings Papers on Economic Activity. 3: 783–831. Washington, D.C.: Brookings Institution Press.

Malerba, F. 1992. “Learning by firms and incremental technical change.” *The Economic Journal.* 102, 413: 845–859.

March, James G. 1981. “Footnotes to organizational change.” *Administrative Science Quarterly.* 26, 4: 563–577.

Marshall, Alfred. 1920. *Principles of Economics: An Introductory Volume*. (8th ed.). New York: Macmillan.

Maskell, P., and A. Malmberg. 1999. “Localised learning and industrial competitiveness.” *Cambridge Journal of Economics.* 23, 2: 167–185.

Mowery, David C. (ed.). 1988*. International Collaborative Ventures in U.S. Manufacturing.* Cambridge, Mass.: Ballinger.

Nelson, Richard R., and Sidney G. Winter. 1982. *An Evolutionary Theory of Economic Change*. Cambridge, Mass.: Belknap Press of Harvard University.

Piore, Michael J., and Charles F. Sabel. 1984. *The Second Industrial Divide: Possibilities for Prosperity*. New York: Basic Books.

Porter, Michael E. 1990. *The Competitive Advantage of Nations*. New York: Free Press.

Porter, Michael E. 1998. *On Competition*. Harvard Business Review Book Series. Boston, Mass.: Harvard Business School Publishing.

Porter, Michael E. 2000. “Location, competition, and economic development: Local clusters in a global economy.” *Economic Development Quarterly.* 14, 1: 15–34.

Powell, Walter W. 1990. “Neither market nor hierarchy: Network forms of organization.” *Research in Organizational Behavior.* 12: 295–336.

Powell, Walter W., and Peter Brantley. 1992. "Competitive cooperation in biotechnology: learning through networks*?"* In *Networks and Organizations: Structure, Form, and Action*. N. Nohria and R.G. Eccles. (eds.). 366–394. Boston, Mass.: Harvard Business School Press.

Reber, A. 1995. *Implicit Learning and Tacit Knowledge: An Essay on the Cognitive Unconscious.* New York: Oxford University Press.

Romeo, A. 1975. "Interindustry and interfirm differences in the rate of diffusion of an innovation." *Review of Economics and Statistics.* 57: 311–319.

Romer, P.M. 1990. "Endogenous technological change." *Journal of Political Economy.* 98, 5: 71–102.

Rosenberg, Nathan. 1982. *Inside the Black Box: Technology and Economics*. Cambridge, U.K.: Cambridge University Press.

Rosenthal, Stuart S., and William C. Strange. 2001. "The determinants of agglomeration." *Journal of Urban Economics*. 50, 2: 191–229.

Rosenthal, Stuart S., and William C. Strange. 2003. "Geography, industrial organization, and agglomeration." *Review of Economics and Statistics.* 85, 2: 377–393.

Saxenian, AnnaLee. 1994, *Regional Advantage: Culture and Competition in Silicon Valley and Route 128*. Cambridge, Mass.: Harvard University Press.

Saxenian, AnnaLee. 1996. "Inside-out: Regional networks and industrial adaptation in Silicon Valley and Route 128." *Cityscape: A Journal of Policy Development and Research.* 2, 2: 41–60. Washington, D.C.: U.S. Department of Housing and Urban Development. Office of Policy Development and Research.

Scherer, Frederic M., Alan Beckenstein, Erich Kaufer, Dennis R. Murphy and Francine Bougeon-Massen. 1975. *The Economics of Multi-plant Operation: An International Comparisons Study*. Cambridge, Mass.: Harvard University Press.

Statistics Canada. n.d. *Annual Survey of Manufactures* (ASM). 1983 to 1993. Ottawa: Statistics Canada.

Statistics Canada, 1993. *Survey of Innovation and Advanced Technology* (SIAT). Ottawa: Statistics Canada.

von Hippel, Eric. 1988. *The Sources of Innovation.* Oxford: Oxford University Press.