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Urban Economies and Productivity

by John R. Baldwin, Desmond Beckstead, W. Mark Brown and David L. Rigby

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Abstract

Productivity levels and productivity growth rates vary significantly over space. These differences are perhaps most pronounced between countries, but they remain acutely evident within national spaces as economic growth favors some cities and regions and not others. In this paper, we map the spatial variation in productivity levels across Canadian cities and we model the underlying determinants of that variation. We have two main goals. First, to confirm the existence, the nature and the size of agglomeration economies—that is, the gains in efficiency related to the spatial clustering of economic activity. We focus attention on the impacts of buyer-supplier networks, labour market pooling and knowledge spillovers. Second, we identify the geographical extent of knowledge spillovers using information on the location of individual manufacturing plants. Plant-level data developed by the Micro-economic Analysis Division of Statistics Canada underpin the analysis. After controlling for a series of plant and firm characteristics, analysis reveals that the productivity performance of plants is positively influenced by all three of Marshall's mechanisms of agglomeration (Marshall, 1920). The analysis also shows that the effect of knowledge spillovers on productivity is spatially circumscribed, extending, at most, only 10 km beyond individual plants. The reliance of individual businesses on place-based economies varies across the sectors to which the businesses are aggregated. These sectors are defined by the factors that influence the process of competition—access to natural resources, labour costs, scale economies, product differentiation, and the application of scientific knowledge. Neither labour market pooling, buyer-supplier networks nor knowledge spillovers are universally important across all sectors. This paper provides confirmation of the importance of agglomeration, while also providing evidence that external economies are spatially bounded and not universally important across all industries.

Keywords: agglomeration economies, localization economies, productivity, urban economies

Executive summary

Productivity levels and productivity growth rates vary significantly over space. These differences are perhaps most pronounced between countries, but they remain acutely evident within national spaces. In this paper, we attempt to account for the spatial variation in productivity levels of manufacturing plants across Canadian cities (census metropolitan areas and census agglomerations).

The paper has two main goals. The first is to confirm the existence, the nature and the size of agglomeration economies—that is, the gains in labour productivity related to the spatial clustering of economic activity. Theoretically, there are three mechanisms through which the geographic concentration of firms in the same industry might raise their performance. First, the geographical clustering of businesses stimulates the development of upstream industries that provide specialized inputs (e.g., machinery and equipment) that can help boost the productivity of a downstream sector. Second, the co-location of firms is often associated with development of relatively large pools of labour embodying skills that are needed by firms within the agglomeration. Firms that do not have access to these pools of specialized labour may have to substitute workers with less appropriate skills, reducing their productivity. Finally, the close proximity of firms is thought to enhance the flow of knowledge, with consequent, positive impacts on productivity. These mechanisms help explain why firms might choose to cluster in space and why productivity may be higher in firms that locate within these concentrations relative to those that locate outside them.

Utilizing plant-level data from the 1999 Annual Survey of Manufactures, and after controlling for a series of plant and firm characteristics, the analysis reveals that the productivity performance of plants is positively influenced by all three mechanisms of agglomeration. Plants are more productive when they are located in cities that are specialized in upstream (input-supplying) industries. Plants are also more productive when there is a close match between the worker skills they require and the skills available in the urban area in which they are located. Finally, plants are more productive when there are a larger number of nearby plants in the same industry, providing more opportunity for the spillover of knowledge across plants.

The second goal of the analysis was to identify the geographical extent of knowledge spillovers. This was tested for by relating the number of surrounding plants to a plant and its level of productivity. The analysis shows that the effect of knowledge spillovers on productivity is spatially circumscribed, extending, at most, only 10 km beyond individual plants. The number of plants located beyond 10 km of a plant had no impact on its productivity levels.

In addition to looking at the impact of agglomeration economies on productivity across the entire plant population, the paper also looked at how these economies affected the productivity of plants in specific sectors. The analysis shows the reliance of individual businesses on place-based economies varies across the sectors to which the businesses are aggregated. These sectors are defined by the factors that influence the process of competition—access to natural resources, labour costs, scale economies, product differentiation, and the application of scientific knowledge. Neither labour market pooling, buyer-supplier networks, nor knowledge spillovers are universally important across all sectors. Yet regardless of which agglomerative forces are

important, in most sectors, one or two had a significant effect on productivity. Hence, the geographic concentration of industry has a positive influence on performance across a broad spectrum of sectors comprising business establishments that rely on very different strategies to maintain their competitive advantage.

1. Introduction

Productivity levels vary dramatically across firms in Canada. We typically account for these differences by noting the industries within which firms operate and by controlling for the characteristics of the businesses themselves. Yet, often after we have performed this exercise, significant differences in performance remain, differences that manifest themselves in distinct geographical patterns. These patterns suggest that factors external to the individual firm, found in some geographical locations and not others, are responsible. One of the main goals of this paper is to identify what these 'external' factors might be.

There is a long tradition of research dating back to Alfred Marshall (1920) that argues firm productivity depends not only on how production is organized within the firm (and its plants), but also on the characteristics of the location at which the firm is found. In short, it is argued that the clustering of economic activity in geographic space yields advantages to firms that are unavailable to businesses that choose more isolated locations. These advantages are thought to sustain the well-known agglomerations of economic activity that punctuate the landscapes of most industrialized nations (Scott, 1988). In turn, the existence of these agglomerations has stimulated a large literature that seeks to identify the mechanisms by which co-location benefits firms, and to measure their effects on productivity. In this paper, we focus on processes of agglomeration identified by Marshall.

Marshall identified three mechanisms through which the geographic concentration of firms might raise their performance. First, the geographical clustering of businesses stimulates the development of upstream industries that provide specialized inputs (e.g., machinery and equipment) that can help boost the productivity of a downstream sector. Second, the co-location of firms is often associated with development of relatively large pools of labour embodying skills that are needed by firms within the agglomeration. Firms that do not have access to these pools of specialized labour may have to substitute workers with less appropriate skills, reducing their productivity. Finally, the close proximity of firms is thought to enhance the flow of knowledge, with consequent, positive impacts on productivity. These mechanisms help explain why firms might choose to cluster in space and why productivity may be higher in firms that locate within these concentrations relative to those that locate outside them.

In this paper, we test Marshall's three sources of agglomeration economies by utilizing micro-data on individual manufacturing plants. We show how productivity differences across business establishments reside in plant-specific and place-specific characteristics. We go on to explore the nature and magnitude of agglomeration economies—that is, the gains to productivity that are produced in discrete locations, and to determine the geographical scope of knowledge spillovers, a key source of competitive advantage. Those tasks occupy four sections of the paper. In Section 2 we provide a brief overview of past research on agglomeration. Section 3 discusses the establishment-level data, developed by the Micro-economic Analysis Division of Statistics Canada, which underpins our research. Section 4 presents some descriptive statistics and the main results of our analysis. Section 5 summarizes our findings and discusses extensions of this research.

2. Literature

The observed spatial concentration of much economic activity is generally employed as a marker of place-based economic advantage. Where firms locate in order to access geographically localized sources of natural resources, the advantage that certain locations bring is clear. Outside the resource sector, however, the precise form of the economies that firms derive from spatial association has been less easy to document (Rosenthal and Strange, 2001) and fraught with some nagging difficulties (Rigby and Essletzbichler, 2002).

Externalities produced by the geographical clustering of economic activity are commonly divided into two types. Localization economies are produced when firms within the same industry co-locate, these efficiencies flowing only to businesses in that same industry. Urbanization economies are more general advantages that result from scale, from the agglomeration of all business activities in a particular place.[1] Urbanization economies are available to all firms sharing a common location, regardless of industry affiliation. Though Rigby and Essletzbichler (2002) complain that the distinction between localization and urbanization economies tends to obscure analysis of the specific mechanisms by which externalities are produced and distributed, it does have the virtue of focusing attention on the importance of specialization vis-à-vis diversity.

As the interest in agglomeration has shifted from a static framework for understanding the formation and character of cities (Henderson, 1986), toward dynamic models of local economic growth increasingly driven by externalities (Glaeser et al., 1992), research has refocused on the characteristics of urban and regional economies that enhance knowledge production and diffusion. Two opposing views dominate this literature. According to the so-called MAR model, a composite of the works of Marshall (1920), Arrow (1962) and Romer (1986), the benefits of agglomeration flow most freely within specialized clusters of firms from the same industry. Jacobs (1969) hinges the competing vision, offering a model of urban economic growth with industrial diversity at its core. More sophisticated variants of these basic claims have emerged, adding life cycles of technologies and industries, arguing that economically diverse environments favour development of new technologies and industries, but that once standardized, more specialized environments enhance growth (Henderson, Kuncoro and Turner, 1995; Duranton and Puga, 2000).

Empirical work on agglomeration might be broadly understood as falling into two stages. The first stage of investigation, using aggregate data for metropolitan areas and U.S. states, sometimes disaggregated to the (two-digit Standard Industrial Classification [SIC]) industry level, explored the influence of industry scale and population size (Sveikauskas, 1975; Carlino, 1978; and Moomaw, 1981, 1983b), the urban proportion of a state’s population (Beeson, 1987; Beeson and Husted, 1989; Williams and Moomaw, 1989; and Moomaw and Williams, 1991), or employment density (Ciconne and Hall, 1996) on productivity levels or productivity growth rates. Results from these studies are mixed, though there is more support for the existence of localization economies resulting from the spatial concentration of firms in the same industry,

1. See Duranton and Puga (2003) for an extensive discussion of the micro-foundations of urban agglomeration economies.

than for urbanization economies resulting from industry diversity or the concentration of overall economic activity. Moomaw (1983a) and Gerking (1994) review this early work.

A second, more recent, stage of analysis has focused on the identification and measurement of different forms of the returns to agglomeration after Marshall (1920). This stage of inquiry also has been characterized by its use of more sophisticated sources of data, particularly establishment-level data, or micro-data. Using the U.S. Census Bureau's Longitudinal Research Database (LRD), Dumais, Ellison and Glaeser (1997) examine the recent history of geographical concentration in U.S. manufacturing sectors. They show concentration levels have remained relatively constant in spite of a great deal of underlying turbulence in terms of plant turnover and differential growth. They go on to explicitly test for Marshall's three sources of agglomeration economies—cost-savings due to local networks of buyers and suppliers, labour market pooling and technology spillovers. Focusing on industry co-agglomeration patterns, they find limited support for all Marshallian agglomeration forces, though the labour market effect dominates. The strength of the labour market pooling argument is confirmed by Rosenthal and Strange (2001) who use Dunn and Bradstreet data to explain the degree of industry concentration at different spatial scales across the United States. In a later paper using the same data, though limited to a small number of industrial sectors, Rosenthal and Strange (2003) focus on the geographical scale at which localization (own industry) economies and urbanization (cross-industry) economies operate. Using counts of business units in different industries at zip-code, county and state scales, they show that localization economies attenuate rapidly with distance. Rigby and Essletzbichler (2002) exploit the LRD to examine the existence of Marshall's agglomeration economies across industries and metropolitan areas of the United States. Borrowing measures of those economies from Dumais, Ellison and Glaeser (1997) and taking explicit account of spatial dependence in the data, their results provide strong support for Marshall's claims. They also show how the strength of those arguments varies across manufacturing industries at the two-digit SIC level. Henderson (2003) also employs LRD data to build plant-level production functions for different sectors, controlling for unobserved plant heterogeneity with fixed effects panel models. His work shows the importance of localized knowledge spillovers, of a MAR kind, based on the positive influence of counts of plants in the same industry and county on output. Little support is offered to support Jacobs' (1969) externalities.

We seek to extend these arguments using plant-level data for Canadian manufacturing. We have two broad aims. The first is to explore the relative size and the significance of different forms of agglomeration operating across the Canadian space-economy. The second is to examine the geography of knowledge spillovers using latitude and longitude data to fix the location of individual plants. Like Henderson (2003), we estimate, at least implicitly, plant-level production functions (see Appendix 1), controlling for plant characteristics to isolate the effects of different agglomeration factors. Like Rosenthal and Strange (2003), we attempt to identify the geographical scope of localization economies, focusing on local geographies of intra-industry plant location. Unlike Henderson (2003) and Rosenthal and Strange (2003), our analysis is not restricted to a limited number of industrial sectors.

In Canada, there have been few previous attempts to examine the operation of agglomeration economies (Auer, 1979; Anderson, 1990; and McCoy and Moomaw, 1995). McCoy and Moomaw (1995) test the effect of urban size on productivity across Canadian cities. They find productivity highly correlated with the size of population. Focusing on regional productivity variations within the manufacturing sector, Anderson (1990) also finds indirect evidence consistent with the existence of agglomeration economies. The current research differs from previous work on agglomeration economies in Canada because it seeks to identify and measure various mechanisms through which the geographical concentration of economic activity boosts productivity. Our work may also be distinguished by its focus on plant-level data. These data allow us to control directly for plant- and firm-specific characteristics, and thus focus attention on the attributes of particular economic spaces that impact the performance of individual business units.

3. Data and econometric specification

The analysis reported below is based upon unpublished manufacturing establishment-level data derived from a longitudinal micro-data file from Statistics Canada's Annual Survey of Manufactures.[2] The potential of longitudinal micro-data, or panel micro-data, are outlined in Baily, Hulten and Campbell (1992), Bartelsman and Doms (1997), Baldwin (1995) and Foster, Haltiwanger and Krizan (1998). Baldwin (1995) and Baldwin et al. (2001) discuss the construction of the Canadian micro-data and reveal a good deal of their utility. In addition to these micro-data, the analysis also utilizes variables derived from the 1996 Census of Population to provide information on metropolitan area (census metropolitan area and census agglomeration) characteristics.

We use the micro-data to estimate a series of regression models that examine labour productivity variations across approximately 20,000 Canadian manufacturing establishments for 1999. Because of the problem of outliers in plant-level data, we focus only on those plants with labour productivity values between the 5th percentile ($19,000) and the 95th percentile ($274,000). Labour productivity (LP) is defined as annual manufacturing value-added per production worker. Our explanatory variables comprise a series of plant-specific and metropolitan-area-specific characteristics. We control for sectoral variations in labour productivity using industry fixed-effects dummy variables, primarily at the three-digit level of the 1980 Canadian Standard Industrial Classification. We also add provincial dummy variables to control for broad geographical differences in productivity levels.

Our analysis examines the effects of both plant and firm characteristics and metropolitan area or local geographical characteristics on labour productivity at the plant level. Our model takes the following simple linear form,

$$LP_{im} = \alpha + \mathbf{X}_{im}\beta + \mathbf{Z}_m\delta + \varepsilon_{im} \ , \qquad (1)$$

where $\mathbf{X}_{im}$ is a vector of plant-specific characteristics indexed by i (e.g., plant size). The subscript m indexes the city in which the plant is found. $\mathbf{Z}_m$ is a vector of city- or geography-based characteristics indexed by m (e.g., city population), and ε_{im} is an error term. To ease

[2] Under the Statistics Act, these data are confidential.

interpretation of model results, all continuous variables are logged (see Appendix 1 for a derivation of the model).

Typically, we assume that $E(\varepsilon) = 0$ and that $E(\varepsilon\varepsilon') = \sigma^2$. However, when aggregate geographical data (our measures of agglomeration economies) are distributed across micro-level units (our plant-level observations), there may be substantial correlation of disturbance terms across the micro-level units that share the same values of the aggregate variable (see Moulton, 1990). In this case, we know

$$E(\varepsilon\varepsilon') = \sigma^2\mathbf{V} = \sigma^2[(1-\rho)\mathbf{I}_n + \rho\mathbf{W}\mathbf{W}'] \ , \qquad (2)$$

where ρ is the intraclass correlation of the disturbances; that is, the correlation of elements of ε that share the same value of the aggregate variable (belong to the same aggregate group), and $\mathbf{W}$ is an *n* x *m* matrix of 0-1 values indicating membership in each of the *m* groups of the aggregate variable.

When derived from data with correlated disturbances, coefficient estimators are unbiased, but inefficient, while standard errors are biased. In this case, the true variance-covariance matrix of the OLS estimator of β is no longer $\sigma^2(\mathbf{X}'\mathbf{X})^{-1}$, but rather

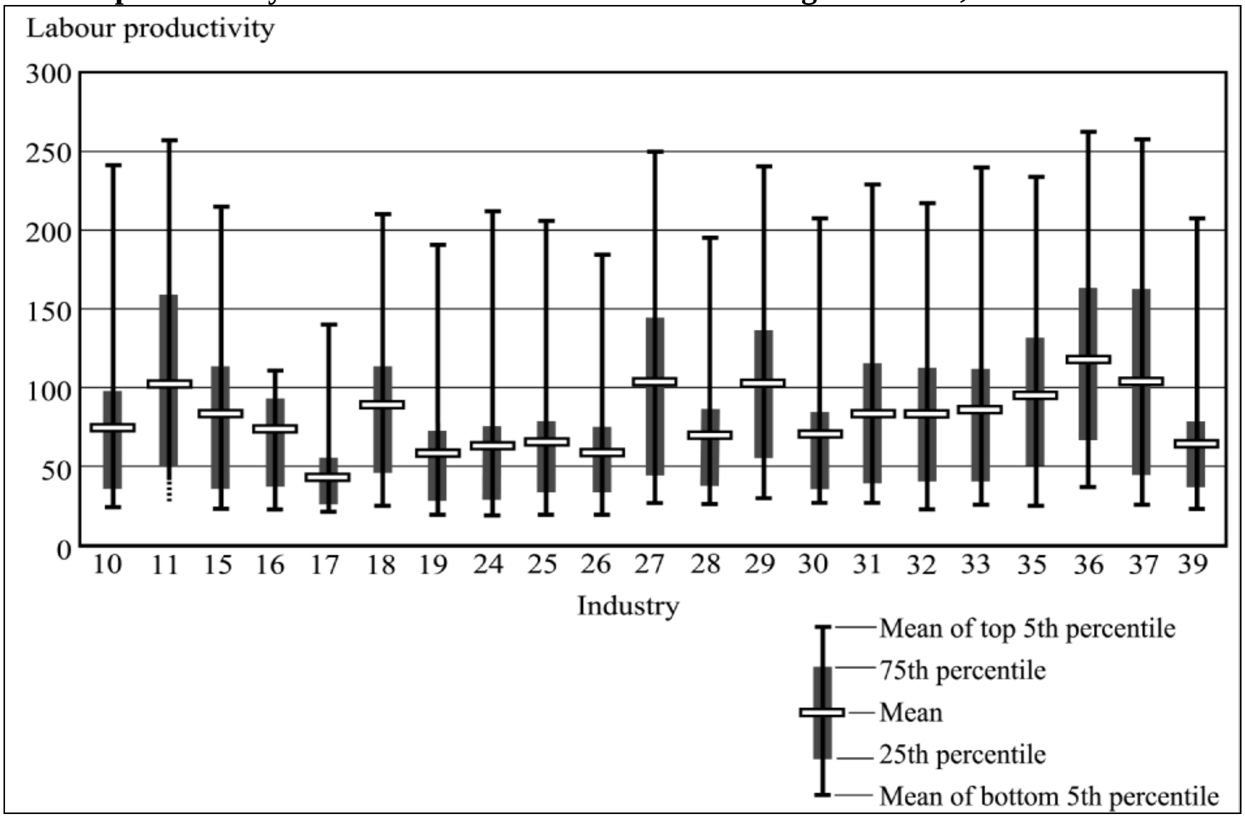
$$\sigma^2(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{V}\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1} \ . \qquad (3)$$

Note that we employ this correction for correlated disturbance terms in our estimation, when noted.

4. Results

Figure 1 shows the range of values of labour productivity in Canadian manufacturing. In this figure, individual firms have been assigned to one of the main two-digit Standard Industrial Classification (SIC) industrial groupings. For each industry, mean productivity levels, the interquartile range and the mean of the top and bottom 5th percentiles are reported. There are too few observations to present results for the tobacco industry without the disclosure of confidential information. Similarly, the mean of the bottom percentile for the beverage industry cannot be shown. The figure reveals substantial variations in productivity values across industrial sectors. For example, the mean level of labour productivity in the refined petroleum and coal products industry is more than twice as high as that found in the leather, textile products, clothing and furniture industries. Across industries, there is more variation in productivity values at the top end of the productivity distribution than at the bottom end. Figure 1 also illustrates the diversity of productivity values within each industry. Diversity is particularly high (range/mean > 2.9) within the clothing, textile and wood industries and is relatively high in the food and furniture sectors.

Figure 1
Labour productivity variations in Canadian manufacturing industries, 1999



Note: The two-digit 1980 Standard Industrial Classification manufacturing industry groupings are as follows: 10: Food, 11: Beverage, 15: Rubber products, 16: Plastic products, 17: Leather and allied, 18: Primary textile, 19: Textile products, 24: Clothing, 25: Wood, 26: Furniture and fixtures, 27: Paper and allied products, 28: Printing and publishing, 29: Primary metals, 30: Fabricated metal products, 31: Machinery, 32: Transportation equipment, 33: Electrical and electronic products, 35: Non-metallic mineral products, 36: Refined petroleum and coal products, 37: Chemical products, 39: Miscellaneous products.
Source: Statistics Canada, Annual Survey of Manufactures.

Within each of these broad industrial groups, there is significant variation in economic performance. For the most part, these variations in productivity can be explained by the characteristics of individual plants and their respective firms. We test for the effect of plant and firm characteristics on productivity by estimating a base model that includes only a vector, $\mathbf{X}_{im}$, of plant- and firm-specific characteristics.

Table 1 provides a summary of the plant- and firm-level variables that we include in the base model. These variables can be divided into two groups. The first describes the characteristics of individual plants. Labour productivity is expected to be higher in plants that are larger in size because they are able to take advantage of various forms of scale economies (e.g., those that result from longer production runs). Plant size is measured by the number of production workers (EMP). The labour productivity of production workers is also expected to rise as the amount of machinery and equipment they work with increases. We would like to capture the effect of mechanization with a variable measuring the capital/labour ratio. Unfortunately, capital stock data are unavailable at the plant level; we therefore use a proxy variable, the ratio of profits to value-added (P/VA), to represent the capital/labour ratio. Justification for this proxy is provided in Appendix 1. Production workers tend to generate higher levels of output if more non-production workers are contributing to the production process. For instance, more input from management and engineering functions can help to improve the organization of the production process. Hence, we expect labour productivity to be positively associated with the ratio of non-production workers to production workers (NPWPW).

Table 1
Plant characteristic variables

Variables	Description
EMP	Number of production workers
P/VA	Ratio of profit to value-added (proxy for capital/labour ratio)
NPWPW	Ratio of non-production workers to production workers
AGEYR	Binary variable with 1 indicating that the plant was born in the decade given by year
GREENYR	Binary variable with 1 indicating that the plant was a new firm entrant in the decade given by year
MULTI	Binary variable with 1 indicating that a plant is part of a multi-plant firm
FOWN	Binary variable with 1 indicating that a plant is part of a foreign-owned firm

Notes: Capital stock data are unavailable at the plant level and so the capital/labour ratio of plants cannot be directly measured. Appendix 1 explains our use of the profit/value-added ratio as a proxy for the capital/labour ratio.

Productivity can also be influenced by the age of plants. On the one hand, older plants may utilize outdated equipment that would tend to lower their relative labour productivity. On the other hand, older plants are also those that have survived, and survival is a strong indicator that these establishments have remained profitable. In turn, this profitability may be associated with re-investment in the plant, either through retained earnings or infusions of capital from outside. Hence, our expectation regarding the sign of the relationship between plant age and productivity is ambiguous. We measure plant age through a series of binary variables (AGEYR) that indicate whether a plant was born in the 1970s, 1980s or 1990s. Each of the AGEYR binary variables is mutually exclusive, and the excluded category is plants born prior to 1970.

Our second group of variables characterizes the firms that control individual plants. We measure three types of firm characteristics in the model. First, we identify whether the plant is part of a multi-plant firm (MULTI). Our expectation is that multi-plant firms will be larger than single-plant firms. Firm size brings the benefit of firm-wide economies to the plant. For instance, larger firms may be better able to collect and analyze information that can improve management practices. Second, we identify whether plants are foreign-owned (FOWN). Foreign-owned plants are expected to have higher levels of productivity because they have access to a broader range of expertise and technologies. The final firm characteristic that we examine is whether or not a plant that was born in the 1970s, 1980s or 1990s is born to a new firm rather than an incumbent. New, or greenfield, firms are often unsure of the physical and human capital they need to produce their output or how they should be combined. As a consequence, it can take new firms a long time before they are able to match the performance of incumbent firms (see Baldwin, 1995). Hence, our expectation is that plants created by new firms will exhibit lower levels of productivity than plants born to incumbent firms. As the plants of new firms age, they should also experience productivity growth. The binary variables (GREENYR) capture whether a plant was born[3] to a new firm in the 1970s, 1980s or the 1990s.

The influence of plant and firm characteristics on plant-level productivity is shown in Table 2. The dependent variable is the logarithm of labour productivity. Model 1 shows the influence of the independent variables in the absence of industry and province fixed effects. Model 2 adds provincial fixed effects, and Model 3 adds industry and province fixed effects along with a correction for possible correlation of error terms across plants within the same metropolitan area. All results are shown with robust standard errors. Industry and province fixed effects exert little influence on the overall story that is by now well-known. The basic arguments of that story are that larger, more capital-intensive plants that employ higher proportions of non-production workers to production workers are more productive. In addition, establishments that are part of a multi-establishment firm and that are foreign-owned are more productive than single-establishment firms and domestic firms.

Table 2
Regressions of labour productivity on plant characteristics, 1999

Variables	Model 1		Model 2		Model 3	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
Intercept	11.41	0.000	11.42	0.000	11.45	0.000
P/VA	0.859	0.000	0.874	0.000	0.901	0.000
EMP	0.036	0.000	0.036	0.000	0.037	0.000
NPWPW	0.321	0.000	0.321	0.000	0.275	0.000
MULTI	0.237	0.000	0.241	0.000	0.190	0.000
FOWN	0.177	0.000	0.172	0.000	0.131	0.000
AGE70	-0.005	0.628	-0.01	0.312	-0.001	0.940
AGE80	0.011	0.406	0.003	0.821	0.001	0.910
AGE90	0.080	0.000	0.075	0.000	0.059	0.000
GREEN70	-0.041	0.001	-0.04	0.001	-0.051	0.001
GREEN80	-0.077	0.000	-0.74	0.000	-0.064	0.000
GREEN90	-0.133	0.000	-0.134	0.000	-0.115	0.000
Industry fixed effects	No		No		Yes	
Province fixed effects	No		Yes		Yes	
Clustering by CMA/CA[1]	No		No		Yes	
Number of observations	20,424		20,424		20,424	
Adjusted R-squared	0.57		0.58		0.66	
Root MSE	0.324		0.3208		0.2915	

1. Census metropolitan area/census agglomeration.
Notes: All variables are logged with the exception of the categorical variables on the right-hand side. Units of observation are individual manufacturing plants. The variables shown in this table are described in Table 1. "Root MSE" represents the standard error about the regression. Industry fixed effects include dummies at the three-digit Standard Industrial Classification level for all regressions where noted. All p-values are corrected for heteroskedasticity.
Source: Statistics Canada, Annual Survey of Manufactures.

3. Birth here is associated with the creation of a firm via the building of new plants, not via merger or acquisition of a plant. For more discussion of this distinction see Baldwin (1995).

Also included in the base model are measures of plant and firm age. Since plants that are born in a given decade include those built by continuing firms and new firms, it is important to control for both when the plant was born and whether it was built by a new firm. The results in Table 2 indicate that there is little effect of plant age on productivity, prior to the 1990s. That is, new plants created by incumbent firms—those firms that existed in the previous decade—regardless of whether they were created in the 1970s or the 1980s are as productive as plants built by incumbent firms prior to 1970. Plants born to established firms in the 1990s display significantly higher levels of productivity than plants built by incumbent firms prior to 1970. The difference in the 1990s is likely due to restructuring associated with the North American Free Trade Agreement was occurring. Table 2 also reveals that plants built by new firms had significantly lower levels of productivity than plants built by continuing firms. This pattern holds for all three decades. In sum, these results suggest that the age of the firm is a more important determinant of productivity than is the age of the plant.

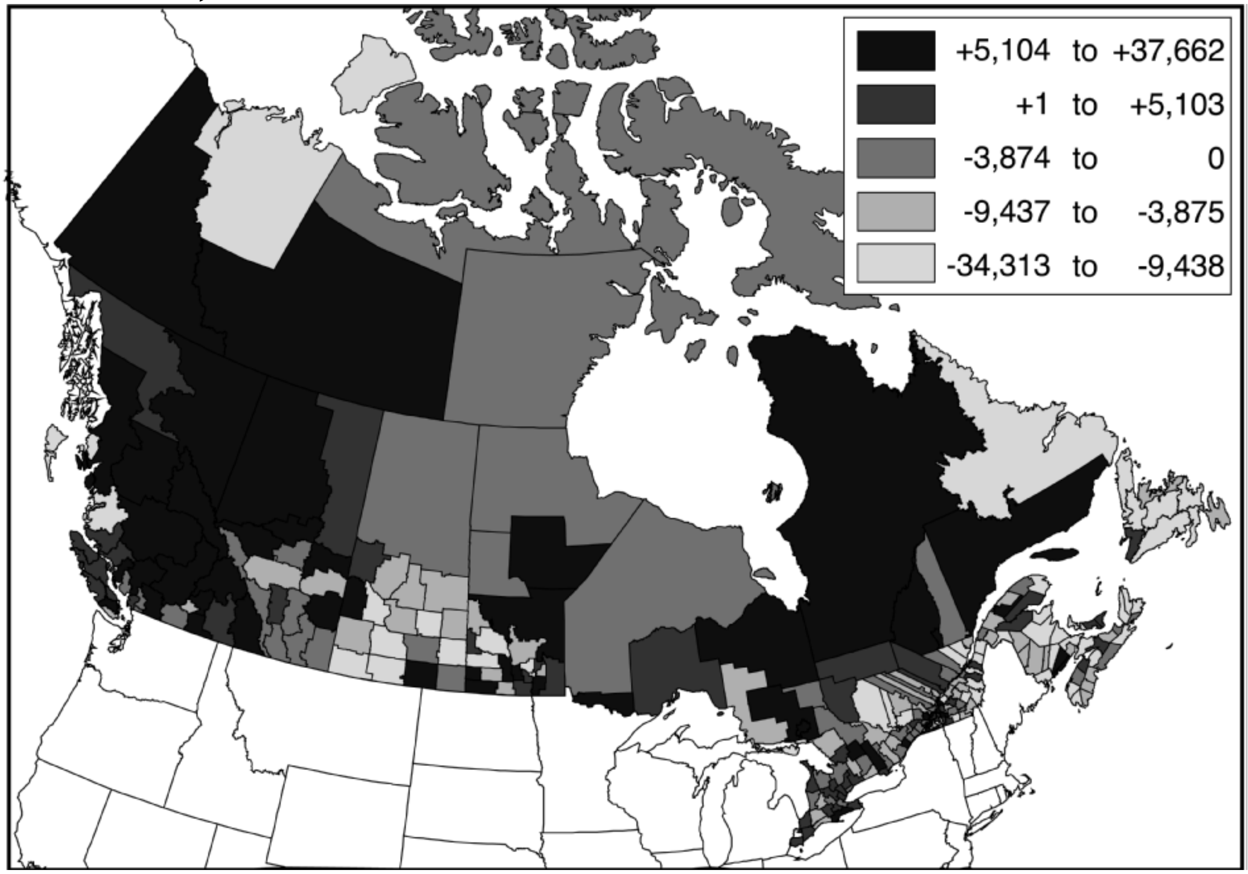
After controlling for the influence of industry fixed effects and the characteristics of individual firms and plants, it is natural to ask how much of the productivity differences depicted in Figure 1 have been accounted for. The coefficients of determination listed in Table 1 provide part of the answer, suggesting that somewhere between a half and a third of the variability in productivity levels remains. An immediate question is whether the remaining variation is simply random noise or whether it has a particular structure. In Figure 2, we explore whether geography, at the census division level,[4] provides more than an *ad hoc* framework for understanding productivity differences between manufacturing plants.

The map (see Figure 2) displays plant-level residuals from Model 2 of Table 2, aggregated up to the census division level. Figure 2 suggests that there are organized spatial variations in productivity levels not accounted for by plant characteristics or industry fixed effects. There is an east-west gradient to the value of the residuals, possibly reflecting the quality of resources available for processing activities found in different parts of the country, which in turn may influence their relative levels of efficiency. Atlantic Canada stands out as a region of relatively low productivity, along with Saskatchewan and parts of rural Quebec. Outside western regions, southern Ontario and southern Quebec around Montréal stand out as centers of above-average productivity. The spatial associations that we observe visually are confirmed by Moran's coefficient of spatial autocorrelation that has a value of 0.223 for the census division map of productivity residuals. This value is significant at the 0.01 level, based on the randomization assumption, and indicates statistically significant spatial clustering of census divisions with similar residual productivity values.

Our job now is to see if we can explain some of the geographical variation in plant productivity residuals using the arguments of agglomeration theory discussed above. We begin this task by focusing specifically on local buyer-supplier networks, labour market pooling and knowledge spillovers, after Marshall (1920). Before defining how we measure these three mechanisms, it is useful to review in more detail Marshall's three sources of agglomeration economies. With respect to buyer-supplier networks, the growing presence of an industry can induce development of specialized suppliers, whose inputs can be tailored to the requirements of its customers. For instance, a machinery and equipment supplier may develop new and more specialized equipment that improves the productivity of a downstream industry. Hence, the presence of extensive and intensive local buyer-supplier networks may be associated with higher productivity for individual establishments within those networks.

4. Census divisions roughly correspond in size to U.S. counties.

Figure 2
Map of plant productivity residuals after controlling for industry and plant characteristics, 1999



Source: Statistics Canada, Annual Survey of Manufactures.

Localized labour market pooling can enhance productivity in two ways. First, it helps to improve the skills matching process between plants and workers. This allows business units to reduce the time positions are left unfilled. Second, a large labour market increases the incentive for workers to invest in the development of specialized skills required by local industry, since they are more likely to obtain a return from those skills. Both better matching and a higher level of human capital might be expected to raise the productivity of individual plants.

Finally, the local concentration of industry might enhance knowledge spillovers across firms and plants. That is, geographic proximity is thought to improve the flow of information, particularly the movement of tacit information that often requires face-to-face contact (Jaffe, Trajtenberg and Henderson, 1993). As Glaeser et al. (1992) note, that information is likely to spread much more easily across hallways and corridors than across countries and oceans. In turn, the availability of more knowledge and information should give rise to higher levels of productivity. We outline below the variables employed to measure these Marshallian economies, along with indicators used to capture other types of agglomeration economies. The variables are defined in the text and in a separate summary table (see Table 3).

Table 3
Metropolitan area and other location-specific variables

Variables	Description
LABMIX	Measure of similarity between the occupation mix of a plant's industry and that of the metropolitan area
USLQ	Measure of the presence of upstream supply industries within a metropolitan area (own industry excluded)
NP010	Number of plants, in the same 2-digit SIC industry, within 10 km of plant *i*
NP1050	Number of plants, in the same 2-digit SIC industry, from 10 km to 50 km away from plant *i*
POP96	Population of metropolitan area (census metropolitan area/census agglomeration)
POPSQ	Population squared
MP	Market potential of the plant's census division

To measure local variation in the density of upstream connections for each four-digit industry and for each census metropolitan area in Canada, we identify an upstream supplier-weighted location quotient (USLQ):

$$USLQ_j^m = \sum_{i, i \neq j} w_{ij}^n \left(\frac{TVS_i^m / \sum_i TVS_i^m}{TVS_i^n / \sum_i TVS_i^n} \right). \qquad (4)$$

The term within the parentheses is a location quotient for each industry *i* in metropolitan area *m*. The location quotients are calculated using the total value of shipments of each industry and measure the degree to which a particular city is specialized in an industry. A value of less than one would indicate an industry was under-represented in that city, while a value greater than one would indicate the industry was over-represented in that city. The term w_{ij} represents the weight of industry *i* as a supplier of industry *j*—that is, the proportion of all manufactured input purchases by industry *j* supplied by industry *i*. Supplier weights are estimated from inter-industry transactions and are derived from the Canadian national input-output tables. The subscripts *i* and *j* refer to each of the 236 4-digit SIC manufacturing industries, *m* refers to one of 137 metropolitan areas in Canada and *n* refers to the nation. Note that we also removed the influence of the own industry in these measures, by dropping the principal diagonal from the input-output direct coefficients matrix. Metropolitan areas whose economies are specialized in industries that are significant suppliers to industry *j* will have a relatively high USLQ. Hence, USLQ is expected to have a positive effect on labour productivity.

An area's labour pool supports the needs of a particular industry if the occupational distribution of an area corresponds to that of the distribution required by that industry. The labour mix (LABMIX) for an industry within a metropolitan area is defined after Dumais, Ellison and Glaeser (1997) as

$$LABMIX_i^m = \sum_o \left(L_{io} - \sum_{j \neq i} \frac{E_j^m}{E^m - E_i^m} L_{jo} \right)^2, \qquad (5)$$

where o represents an occupation, i and j index industries and m refers to the metropolitan area. L measures the proportion of workers in a particular industry and occupation, while E measures the number of workers in a single industry or in all industries within a metropolitan area. This index is a sum of squared deviations that measures the degree to which the occupational distribution of employment of an industry is matched by the occupational distribution of the workforce in the metropolitan area as a whole, excluding the specified industry. The occupational distribution of industry workers is available at the national level and covers some 47 occupations at the 2-digit level using the 1991 Standard Occupational Classification.

As noted above, we anticipate that a better match between the occupational distribution (demand) in an industry and the occupational distribution of the entire workforce of a metropolitan area (supply) will boost productivity. Improved matches reduce the value of the squared term. Thus, we expect a negative coefficient on this variable in the following regressions.

Note that because the labour mix and buyer-supplier network measures are defined at the metropolitan area level, the values for these variables for a given industry are constant for all plants in that industry and metropolitan area. As we have noted above, this necessitates adjustment of the standard errors in our model, for as Moulton (1990) demonstrates, they can be biased when merging aggregate variables across micro units of observation.

The third agglomeration effect arises from knowledge spillovers that are generated by the close proximity of producers in the same urban area. Measuring knowledge spillovers is notoriously difficult, even impossible as Krugman (1991) claims, for they do not leave a paper trail. Jaffe, Trajtenberg and Henderson (1993) disagree. They argue patent citations can be used to track the spatial limits of knowledge spillovers. Nevertheless, the linking of patent information to the plant-level data that are increasingly used to study agglomeration is surprisingly underdeveloped. Rigby and Essletzbichler (2002) show that knowledge spillovers embodied in intermediate goods enhance the productivity of agglomerated plants, but that sheds little light on the role of disembodied information flows. We spent some time examining the influence of local own- and cross-industry patents, in industries of use and make, on plant labour productivity, but were discouraged by the results that were broadly insignificant. Our measures all used simple counts of patents within metropolitan areas and industries linked to the patent classification rather than citations. Raw patent counts for 1999, earlier years, or groups of years were not significantly related to productivity.

As a result, we follow Henderson (2003) and Rosenthal and Strange (2003), and use counts of plants in specific geographical areas as a proxy for knowledge spillovers. For geographical areas, we used the boundaries of metropolitan areas within which plants were located and we exploited data on the latitude and longitude of individual plants to define concentric circles of varying distances around each. We experimented by counting plants within 5 km thresholds, within 10 km thresholds and within 50 km thresholds. We admit that these distances were chosen arbitrarily (see also Wallsten, 2001), since there is not much theory to suggest over precisely what distances particular kinds of information actually flow. For each plant, we counted establishments within all industries over the different distance bands and we counted only establishments within the same two-digit (SIC) industry.[5] Counts of own-industry establishments across concentric circles of 5 km and 10 km in radius produced very similar results in the regression equations and thus, there does not appear to be a critical boundary in terms of knowledge spillovers between 5 km and 10 km around each plant. We thus employ two concentric ring measures of own-industry plant counts in our regression models, the first extending out to 10 km around each plant (NP010), and the second covering a band from 10 km to 50 km around the individual establishment (NP1050). We anticipate that as the density of plants increases, the potential knowledge spillovers expand and that this expansion is expected to boost plant productivity.

Following the advice of reviewers, for all plants in our sample, we also counted own-industry plants within the same metropolitan area and substituted this measure into Model 3 of Table 6 in place of our concentric ring measures. The resulting coefficient had a value of zero and was insignificant (p-value of 0.375). These findings suggest that physical distance is a more important determinant of knowledge spillovers than local political boundaries. It is unclear whether such boundaries in Canada can be readily differentiated in terms of institutional factors that support or hinder knowledge spillovers. In this sense, we cannot interpret these results as suggesting that physical distance is more important than institutional differences in regulating such spillovers. Moreover, we are cognizant that the geographic proximity variable may capture other effects that influence productivity—such as the quality of labour (either entrepreneurs or skilled employees) of other neighbourhood effects such as infrastructure. More work is required in this area in order to examine the nature of plants in areas where density is highest.

We add metropolitan area (census metropolitan area/census agglomeration) population size taken from the 1996 Census of Population (POP96) to our model as a proxy for urbanization type economies that are not captured elsewhere in our model. The benefits of urban size are many. Large urban economies bring with them greater industrial and occupational diversity that facilitate the transfer of new innovations across industries (Jacobs, 1969). Large population centres also create the demand for infrastructure that can enhance the productivity of all industries (e.g., highways, airports, ports and communications networks). We add to the model the square of the population term to allow for potential non-linearities in the relationship between metropolitan area size and plant productivity.

Finally, we also include a measure of market potential (MP). Market potential captures the size of the market available to firms after controlling for the effect of distance. It is calculated for each industry i in census division k, and is defined as

$$MP_{ik} = \sum_{l} Y_{il} d_{kl}^{\beta} \exp^{\alpha CANUS} , \qquad (6)$$

5. Counting establishments in the same three-digit or four-digit Standard Industrial Classification (SIC) industry groups produced very large numbers of zeros for all concentric distance bands.

where Y_{il} is the final demand[6] for the output of (two-digit) industry i in region (census division or U.S. county) l, d_{kl} is the distance between k and l and CANUS is a dummy variable for whether the region pair includes a U.S. county. The parameter estimates for β and α are derived from the industry-level gravity models estimated in Brown and Anderson (2002). Each plant is assigned the market potential of the census division in which it is located. Since the parameter estimate for β is always negative, plants that are located closer to relatively larger markets will have a higher market potential than those located in more remote locations. Market potential is typically highest in larger cities and Southern Ontario, which is well situated with respect to the Canadian and U.S. markets. Market potential is expected to be positively associated with plant size. As such, its effect on productivity will tend to be absorbed by the plant size variable. Nevertheless, plant size may not completely capture the effect of market potential on productivity, since proximity to larger markets may also affect how production is organized within plants (e.g., fewer varieties produced).[7]

Table 4 provides descriptive statistics for the continuous variables employed in our models. These statistics provide mean values and standard deviations for the variables in raw, rather than logged form. Table 5 reports correlation coefficients between these variables along with associated measures of statistical significance. Because of the large number of observations, the p-values are frequently significant, even though the correlation coefficients themselves are relatively low. Those coefficients reach their highest values for relationships between population size and plant counts, as might be expected. Of course, collinearity between variables does not bias our estimators, merely rendering them inefficient. One important issue that is not directly addressed in this paper is omitted variable bias, possibly resulting from the correlation of the quality of firm management with our agglomeration variables. We attempt to address this problem by including variables that might be associated with firm quality such as whether plants are part of a multi-plant firm or they are foreign-owned. In a subsequent paper, we will confront this issue using time-series of our cross-section of plants to sweep away plant-level heterogeneity in a fixed-effects panel specification.

6. This demand for each U.S. SIC1987 two-digit manufacturing sector is estimated using the U.S. 1987 Benchmark input-output accounts applied to both Canadian census divisions and U.S. counties.
7. Baldwin and Gu (2006), building on Melitz (2003), illustrate how trade influences the organization of production within plants.

Table 4
Descriptive statistics, 1999

Variables	Mean	Standard deviation	Number of observations
LP[1]	$78,168	$44,897	20,424
P/VA	0.58	0.16	20,424
EMP	45	132	20,424
NPWPW	0.42	0.46	20,424
LABMIX	5.5	22.0	4,592
USLQ	5.5	2.3	4,592
NP010	68	95	20,424
NP1050	203	259	20,424
POP96	678,043	459,839	133
MP	883,741	1,307,829	1,493

1. Labour productivity.

Notes: Descriptive statistics for the labour mix and the upstream location quotient are calculated across census metropolitan areas/census agglomerations (CMAs/CAs) by three-digit Standard Industrial Classification (SIC) industry, while the ones for market potential are calculated across CMAs/CAs by two-digit SIC industry. The population descriptive statistics are calculated across CMAs/CAs only. The explanatory variables shown in this table are described in Tables 1 and 3.

Sources: Statistics Canada, Annual Survey of Manufactures and 1996 Census of Population.

Table 5
Correlation matrix for continuous variables, 1999

	LP[1]	P/VA	EMP	NPWPW	LABMIX	USLQ	NP010	NP1050	POP96	MP
LP	1									
P/VA	0.5667	1								
	(0.0000)									
EMP	0.3029	0.1143	1							
	(0.0000)	(0.0000)								
NPWPW	0.0763	0.2744	-0.3945	1						
	(0.0000)	(0.0000)	(0.0000)							
LABMIX	-0.0572	-0.0200	0.1053	-0.1496	1					
	(0.0000)	(0.0000)	(0.0000)	(0.0000)						
USLQ	0.1214	0.0784	0.2709	-0.0969	0.0504	1				
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)					
NP010	-0.0418	-0.0103	-0.0298	0.0457	0.0810	0.1038	1			
	(0.0000)	(0.1416)	(0.0000)	(0.0000)	(0.0000)	(0.0000)				
NP1050	-0.0127	-0.0223	-0.0136	0.0425	-0.0256	0.0198	0.6003	1		
	(0.0708)	(0.0014)	(0.0518)	(0.0000)	(0.0000)	(0.0046)	(0.0000)			
POP96	-0.0240	0.0207	-0.0261	0.0846	0.0338	-0.0581	0.6460	0.6970	1	
	(0.0006)	(0.0031)	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		
MP	-0.0162	0.0728	0.0972	0.0609	0.1279	0.0026	0.0327	0.0425	0.1452	1
	(0.0211)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.7138)	(0.0000)	(0.0000)	(0.0000)	

1. Labour productivity.

Notes: Pairwise comparisons are based on the logged values of all variables. P-values are in parentheses. The explanatory variables shown in this table are described in Tables 1 and 3.

Sources: Statistics Canada, Annual Survey of Manufactures and 1996 Census of Population.

Table 6 reveals the impact of the different forms of agglomeration on labour productivity across Canadian manufacturing plants. Once more, results are shown without industry or province fixed effects (Model 1), with industry fixed effects but not province fixed effects (Model 2), and with industry and province fixed effects (Model 3). Comparing Table 2 and Table 6 shows that the effects of plant characteristics on labour productivity change only slightly when we add the agglomeration variables to the regression model.[8] We focus attention here on Model 3 that incorporates both industry and province fixed effects. Turning to the agglomeration measures, the main mechanisms noted by Marshall are all statistically significant with the right sign. First, the labour mix variable has a negative sign indicating that better matching of labour supply with demand raises productivity. This result confirms the findings of Dumais, Ellison and Glaeser (1997) and Rigby and Essletzbichler (2002) in the United States. Note also the relatively large size of the coefficient on the labour mix variable. This coefficient, measuring the elasticity of labour productivity with respect to the labour mix variable, is consistently larger in size than that of most plant characteristics. Clearly, agglomeration economies can play an important role in plant performance. Second, the positive sign on the upstream location quotient indicates that plants benefit from the local presence of establishments in industries that are strongly connected through input-output linkages to the plant's own industry. Third, turning to our measure of knowledge spillovers, plant productivity increases with the number of own-industry surrounding plants located within a 10 km radius. Increases in own-industry plant counts at distances between 10 km and 50 km have no significant impact on productivity. These results confirm the localized nature of knowledge spillovers and our expectations about their benefits. However, they do not necessarily confirm that the 10 km threshold is the critical distance in terms of the local spillover of knowledge. More work is necessary to identify that distance. These results amplify those of Henderson (2003) and Rosenthal and Strange (2003), and they suggest that working with geographic units with boundaries much further than 10 km apart is unlikely to offer much purchase in terms of identifying knowledge spillovers and examining their influence on agglomeration. This claim supports the findings of Wallsten (2001). In terms of knowledge spillovers, our analysis also shows that physical distance is a more useful measure of the friction of space than are local political boundaries.

Finally, Table 6 reports the effect of population size and market potential on the labour productivity of plants. When controlling for industry and province fixed effects, population size is significant and positively related to plant productivity. Thus, locating within larger urban areas provides a competitive advantage to plants, independent of the agglomeration forces identified above. Those advantages tend to diminish with increases in the urban population. Market potential has the anticipated positive sign, though it is statistically insignificant.

8. Note that the sample of plants used to estimate the models presented in Table 6 is restricted to those plants found in metropolitan areas (census metropolitan areas and census agglomerations). The sample of plants used in Table 2 included plants in both metropolitan and rural areas.

Table 6
Regressions of labour productivity on plant characteristics and agglomeration variables, 1999

Variables	Model 1		Model 2		Model 3	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
Intercept	11.693	0.000	14.347	0.000	12.194	0.000
P/VA	0.869	0.000	0.893	0.000	0.900	0.000
EMP	0.042	0.000	0.033	0.000	0.034	0.000
NPWPW	0.315	0.000	0.271	0.000	0.270	0.000
MULTI	0.226	0.000	0.185	0.000	0.190	0.000
FOWN	0.173	0.000	0.132	0.000	0.130	0.000
AGE70	-0.00300	0.750	0.00300	0.779	-0.00012	0.990
AGE80	0.008	0.513	0.006	0.485	0.0016	0.862
AGE90	0.079	0.000	0.059	0.000	0.058	0.000
GREEN70	-0.046	0.000	-0.053	0.000	-0.052	0.000
GREEN80	-0.075	0.000	-0.067	0.000	-0.064	0.000
GREEN90	-0.132	0.000	-0.111	0.000	-0.113	0.000
LABMIX	-0.100	0.000	-1.648	0.008	-0.837	0.025
USLQ	-0.002	0.724	0.013	0.000	0.012	0.000
NP010	-0.0060	0.199	0.0040	0.299	0.0073	0.005
NP1050	0.0160	0.006	0.0120	0.128	-0.0018	0.680
POP96	0.034	0.655	0.022	0.736	0.077	0.035
POPSQ	-0.0012	0.606	-0.0006	0.809	-0.0027	0.053
MP	-0.0270	0.000	-0.0330	0.210	0.0088	0.715
Newfoundland and Labrador					-0.023	0.302
Prince Edward Island					-0.07	0.002
Nova Scotia					-0.048	0.048
New Brunswick					-0.056	0.123
Quebec					0.018	0.075
Ontario					-0.127	0.000
Saskatchewan					-0.041	0.080
Alberta					-0.022	0.274
British Columbia					0.102	0.000
Industry fixed effects	No		Yes		Yes	
Number of observations	20,424		20,424		20,424	
R-squared	0.59		0.66		0.66	
Root MSE	0.32		0.29		0.29	

Notes: All variables are logged with the exception of the categorical variables on the right-hand side. All p-values are based on robust standard errors, and adjusted for the presence of correlation between error terms of plants located in the same metropolitan area (census metropolitan area/census agglomeration). Model 1 does not include industry or province fixed effects. Model 2 includes industry fixed effects only. Model 3 includes industry and province fixed effects. "Root MSE" represents the standard error about the regression. The explanatory variables shown in this table are described in Tables 1 and 3. Cells have been left empty when variables are not included in the model.

Sources: Statistics Canada, Annual Survey of Manufactures and 1996 Census of Population.

The results to this point suggest agglomeration economies play a significant role in the determination of labour productivity. That being said, there is no guarantee that across all industries agglomeration economies will be important. To examine this issue, we estimate our productivity model for five broad sectors. We do not choose to do so across all three- or four-digit SIC industries for two reasons. First, the number of plants within most three- or four-digit SIC industries in Canada is quite small and so it is difficult to obtain statistically significant results. Second, it would be difficult to make sense of results that stretch across hundreds of sectors. To circumvent these problems, we follow a different course and aggregate industries together into five broad sectors.

These five sectors are taken from the Organisation for Economic Co-operation and Development (OECD, 1987). They are defined as natural-resource-based, labour-intensive, scale-based, product-differentiated and science-based. The original OECD classification was tailored for use with the Canadian manufacturing data. Baldwin and Rafiquzzaman (1994) list the four-digit SIC industries assigned to each of the OECD sectors. Each sector is defined primarily on the basis of the factors that influence the process of competition. For natural-resource-based industries, the primary determinant of competitive success is access to abundant natural resources. For the labour-intensive sector, it is labour costs. For scale-based industries, competition hinges on the length of production runs. In the product-differentiated group, competition depends on an ability to target production to the demands of various markets. Finally, competition in science-based sectors depends on the application of scientific knowledge.

Although it might be possible to develop a set of expectations regarding the effect of agglomeration economies on each of these industrial sectors, our objective here is more modest. It is mainly to take advantage of these logical groupings of industries to test the consistency of the effect of agglomeration economies across them. That said, we will note when our results provide additional insight into the nature of agglomeration economies.

Table 7 shows the results of running our model of labour productivity across plants that are located in each of the five OECD sectors. Once more, these models are estimated across individual plant observations. In all cases, industry and province fixed effects are included. Overall, plant characteristics impact labour productivity in a consistent way across these five industry groupings, though the size of the partial regression coefficients are variable. However, the different types of agglomeration economies operate quite unevenly.

Table 7
Regression of labour productivity on plant characteristics and agglomeration variables across metropolitan areas for OECD[1] industrial classes, 1999

Variables	Natural-resource-based		Labour-intensive		Scale-based		Product-differentiated		Science-based	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
Intercept	11.265	0.000	12.163	0.000	12.616	0.000	12.311	0.000	13.674	0.000
P/VA	0.918	0.000	1.037	0.000	0.813	0.000	0.842	0.000	0.856	0.000
EMP	0.027	0.000	0.033	0.000	0.039	0.000	0.043	0.000	0.026	0.055
NPWPW	0.242	0.000	0.294	0.000	0.231	0.001	0.219	0.009	0.348	0.000
MULTI	0.202	0.000	0.176	0.000	0.204	0.000	0.166	0.000	0.163	0.000
FOWN	0.113	0.000	0.143	0.000	0.13	0.000	0.101	0.000	0.202	0.000
AGE70	-0.019	0.419	0.028	0.287	-0.047	0.012	0.038	0.046	0.051	0.057
AGE80	-0.017	0.442	0.04	0.158	0.0003	0.988	0.018	0.615	-0.021	0.559
AGE90	-0.023	0.292	0.135	0.003	0.071	0.065	0.134	0.014	0.113	0.008
GREEN70	-0.037	0.167	-0.071	0.003	0.0007	0.986	-0.083	0.000	-0.081	0.002
GREEN80	-0.067	0.001	-0.092	0.001	-0.056	0.003	-0.076	0.063	-0.001	0.974
GREEN90	-0.039	0.080	-0.184	0.000	-0.132	0.003	-0.191	0.001	-0.126	0.002
LABMIX	-0.606	0.058	-0.865	0.039	-0.631	0.240	-1.0955	0.027	-0.918	0.158
USLQ	0.015	0.002	0.013	0.099	0.014	0.000	0.001	0.745	0.005	0.468
NP010	-0.0035	0.285	0.015	0.000	0.008	0.266	0.01	0.024	0.001	0.580
NP1050	-0.008	0.201	0.006	0.458	-0.008	0.132	-0.0014	0.819	0.005	0.688
POP96	0.104	0.065	0.100	0.065	-0.008	0.882	0.0955	0.066	0.065	0.526
POPSQ	-0.0035	0.108	-0.004	0.058	0.0009	0.660	-0.0035	0.076	-0.0025	0.547
MP	0.04	0.104	-0.0003	0.991	-0.006	0.873	0.021	0.645	-0.102	0.370
Number of observations	5,372		5,157		4,372		3,934		1,589	
Adjusted R-squared	0.71		0.65		0.66		0.6		0.6	
Root MSE	0.29		0.29		0.28		0.28		0.31	

1. Organisation for Economic Co-operation and Development.
Notes: All models include industry and province fixed effects. “Root MSE” represents the standard error about the regression. The explanatory variables shown in this table are described in Tables 1 and 3.
Sources: Statistics Canada, Annual Survey of Manufactures and 1996 Census of Population.

No agglomeration economy is universally important across all five sectors. Labour market pooling (LABMIX) has the anticipated sign in all sectors, though it exerts a significant effect on productivity for only three of the five sectors—natural-resource-based industries, labour-intensive industries and product-differentiated industries. It is also close to significant for science-based industries (p-value of 0.16). In the cases of natural-resource-based industries and product-differentiated industries, these results make intuitive sense. Most of Canada’s natural-resource production takes place in relatively specialized communities, whose occupational mix will tend to be oriented towards the needs of their major resource-based employers. In the product-differentiated sector, design and tailoring of output to specific market needs is critical for competitive advantage and these facets of competition likely rest heavily on skilled labour. In the case of labour-intensive industries, the results are a little surprising. Labour-intensive sectors typically employ relatively large numbers of unskilled workers. It is commonly supposed that such workers are widely available, their skilled counterparts showing a greater tendency to cluster in specific locations. We are similarly surprised that the labour mix variable was not statistically significant for the science-based sector. However, the results for the labour intensive and science-based sectors suggest that labour pooling advantages are inversely related to labour mobility—if the skill level is directly related to mobility.

The strength of buyer-supplier links (USLQ) in a city has positive effects on productivity across all industries, though these effects are only significant in three of the five sectors—natural-resource-based, labour-intensive and scale-based. Upstream resource processing tends to cluster spatially—which may reflect a comparative advantage derived from access to a low-cost/high-quality resource base—hence, the positive and significant coefficient for the buyer-supplier network effect in the resource sector. Within scale-based industries, inventory management has become increasingly important in sustaining profits, and just-in-time and related management practices are likely easier to coordinate and control where the local supplier base is more extensively developed. Within the labour-intensive sector, such as garment production, the limited economies of scale and scope require dense concentrations of upstream and downstream linkages to function (Scott, 1988).

Knowledge spillovers (NP010) have a significant and positive effect on the productivity of plants belonging to labour-intensive and product-differentiated sectors. In the case of the labour-intensive sector, we suspect that our proxy for knowledge spillovers is not picking up what we traditionally think of as information flows in this sector; rather it is capturing the importance of dense local networks of plants in the same two-digit SIC industry that specialize in the quite discrete production tasks found in much labour-intensive manufacturing. Within the product-differentiated sector, knowledge spillovers may be important because of the need to exploit specific product niches that may involve innovation in terms of product design and production processes. And of course, the proximity variable may be picking up other geographic fixed effects.

Urban size, or population (POP96) has a positive impact on productivity in four of the five industries, though it is significant only in natural-resource-based, labour-intensive and product-differentiated industries. Market potential is insignificant across all industries.

There are two broad conclusions to be drawn from analysis across the OECD sectors. The first is that the means by which agglomeration economies affect productivity varies quite markedly across broad industrial groupings. In particular, Marshall's three mechanisms are not universally important to all sectors. The second conclusion is that, regardless of which agglomerative forces are important, in most sectors, one or two had a significant effect on productivity. Hence, the geographic concentration of industry has a positive influence on performance across a broad spectrum of sectors comprising business establishments that rely on very different strategies to maintain their competitive advantage.

5. Conclusion

Productivity levels and productivity growth rates vary significantly over space. In this paper, we map the spatial variation in productivity levels across Canadian cities and we model the underlying determinants of that variation. The paper's overriding goal was not only to confirm the existence of agglomeration economies but to identify the individual processes that underlay these economies. In that regard, we paid particular attention to those mechanisms identified by Marshall—the impacts of buyer-supplier networks, labour market pooling and knowledge spillovers.

After controlling for a series of plant and firm characteristics, we found all three of Marshall's agglomeration economies to be important. Plant productivity tended to be higher in those cities where specialized upstream industries were present, providing an important source of inputs for downstream businesses. Productivity was also higher for plants located in cities where the labour pool mirrored the occupational distribution of the industry to which the plant was affiliated. Finally, the productivity of Canadian manufacturing plants tends to be higher where those plants are surrounded by relatively large numbers of other establishments in similar (two-digit Standard Industrial Classification) industries. In short, the geographic concentration of industry that presumably stimulates and is stimulated by the concentration of upstream suppliers, pools of skilled labour and the exchange of knowledge is an important determinant of labour productivity.

The reliance of firms on place-based economies varies across sectors defined by the factors that influence the process of competition—access to natural resources, labour costs, scale economies, product differentiation, and the application of scientific knowledge. The different forms of agglomeration economies that we identified were not universally important across all sectors. For researchers interested in the influence of agglomeration economies within particular sectors of the economy, attention has to be paid to the most important sources of these economies. In all but one sector, however, agglomeration generates some form of productivity advantage.

In terms of knowledge spillovers, our results show that the number of own-industry establishments within a metropolitan area had no significant influence on plant productivity. We did find that the number of own-industry establishments within 10 km of a plant has a strong, positive influence on performance. Outside 10 km, plant density has little impact. These results suggest that physical distance is more important in terms of knowledge spillovers than political boundaries. In turn, this might indicate that, at the local metropolitan level, institutions influencing knowledge transmission are not highly variable. However, the results may also reflect the fact that Canadian metropolitan areas are quite heterogeneous in size and that this heterogeneity limits our ability to identify a consistent boundary effect.

There are several lines of research that follow from the analysis presented here. The first and most obvious is the question of how quickly knowledge spillovers dissipate as we move away from a plant. Our results suggest that beyond 10 km they are no longer important, but this remains a relatively coarse measure. A more spatially refined measure of knowledge spillovers may be in order.

A second line of future research relates to the effect of agglomeration economies on different types of firms. Firm populations are highly heterogeneous. Industries often accommodate wide variations in the size of firms and ages. It is unclear, for instance, whether knowledge spillovers are as important for large, incumbent, multi-plant firms in comparison to small, new, single-plant firms. The former have likely developed considerable internal capabilities to collect information from far-reaching sources, while the latter may have more limited capabilities and thus rely more on locally available knowledge. A subsequent paper will explore these questions, examining the variability of plants that gain from co-location, as well as investigating the characteristics of the plants with whom they seek to associate.

Finally, our conceptualization of how agglomeration economies influence labour productivity may be too limited. For firms, the transition from small to larger-scale production that often accompanies significant increases in productivity is a very challenging process that involves the application of new technologies and new management practices. The transition to more capital-intensive production is probably equally complicated. The ability of firms to make these transitions may be closely linked to their location through the local expertise of suppliers, managers and labour markets.

Appendix 1

Value-added (VA) can be explained by the following Cobb-Douglas production function:

$$VA = AK^{\alpha} L_{pw}^{\beta} L_{npw}^{\sigma} \ , \tag{A1}$$

where K is a measure of capital input, L_{pw} is the number of production workers employed by the plant and L_{npw} is the number of non-production workers.

With a little manipulation, Equation (A1) may be rewritten as

$$\frac{VA}{L_{pw}} = A\left(\frac{K}{L_{pw}}\right)^{\alpha}\left(\frac{L_{npw}}{L_{pw}}\right)^{\sigma} L_{pw}^{\beta+\alpha+\sigma-1} \ . \tag{A2}$$

The Canadian Annual Survey of Manufactures does not provide estimates of capital for plants. Hence, we generate a proxy for the capital used by each manufacturing establishment $(\hat{K})$. We can estimate $\hat{K}$ from the following expression for profit (π):

$$\pi = VA - wages = r\hat{K} \ , \tag{A3}$$

where r is the rate of return on capital. The profit/labour ratio, $r\hat{K} / L_{pw}$, can be substituted into Equation (A2), and if we assume the rate of return is equalized across plants, then

$$\frac{VA}{L_{pw}} = Ar\left(\frac{\hat{K}}{L_{pw}}\right)^{\alpha}\left(\frac{L_{npw}}{L_{pw}}\right)^{\sigma} L_{pw}^{\beta+\alpha+\sigma-1} \ . \tag{A4}$$

Given this formulation, variation in profits across industries and provinces can be accounted for by industry and province fixed effects.

One of the practical problems with Equation (A4) is that our estimate of the capital/labour ratio and our measure of value-added, by their very construction (both contain valued-added in their numerator and labour in their denominator), are going to be very highly correlated.

As a result, we estimate a slightly different model that includes a capital/value-added ratio

$$VA = Ar\left(\frac{\hat{K}}{VA}\right)^{\alpha} VA^{\alpha} L_{pw}^{\beta} L_{npw}^{\sigma} \ . \tag{A5}$$

This implies that

$$VA = Ar^{\frac{1}{1-\alpha}}\left(\frac{\hat{K}}{VA}\right)^{\frac{\alpha}{1-\alpha}} L_{pw}^{\frac{\beta}{1-\alpha}} L_{npw}^{\frac{\sigma}{1-\alpha}} \ . \tag{A6}$$

Labour productivity can then be defined as

$$\frac{VA}{L_{pw}} = Ar^{\frac{1}{1-\alpha}}\left(\frac{\hat{K}}{VA}\right)^{\frac{\alpha}{1-\alpha}}\left(\frac{L_{npw}}{L_{pw}}\right)^{\frac{\sigma}{1-\alpha}} L_{pw}^{\frac{\beta+\alpha+\sigma-1}{1-\alpha}} \ , \tag{A7}$$

which is the equation we estimate. The coefficients in Table 2 (Model 3) can be used to solve for the values of α, β, and σ, yielding estimates of 0.47, 0.40 and 0.14, respectively. The elasticity of scale is estimated to be 2%. These estimates are broadly in line with aggregate factors shares for the manufacturing sector as a whole. For instance, the actual production-worker wage share of manufacturing value-added is 0.36, which is close to our estimated share of 0.40.

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