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Agglomeration Effects in Ontario's Dairy Farming

Getu Hailu,
Department of Food, Agricultural and Resource Economics,
University of Guelph,
Guelph, Ontario, Canada, N1G 2W1,
Tel: 519-824-4120 ext 53890,
Fax: 519-767-1510,
e-mail: ghailu@uoguelph.ca

B. James Deaton,
Department of Food, Agricultural and Resource Economics,
University of Guelph,
Guelph, Ontario, Canada, N1G 2W1,
e-mail: bdeaton@uoguelph.ca

Abstract. This paper examines the agglomeration hypothesis: i.e., firm productive efficiency is increased by closer proximity to other firms. Using a stochastic input distant function with heteroskedastic inefficiency effects, we find that the density of Ontario dairy farms has a significant positive economic effect on production efficiency. The finding has implications for understanding agricultural firm location and farmer led efforts to preserve agricultural farming activities in some regions.

Keywords: Agglomeration, Stochastic Distance Function, Canada, Dairy

JEL codes: *C5, D1, Q12*

1 Introduction

Productivity differs across Canadian firms and these differences "...manifest themselves in distinct geographical patterns..." (Baldwin, Beckstead, Brown, and Rigby 2007, p. 8). One explanation for geographical differences in the measured productivity is that firms benefit - i.e., from knowledge spillovers, better access to upstream suppliers and/or downstream users - from being locating close to one another (Krugman 1991). The enhanced productivity sustained by the clustering of firms (i.e., relatively higher density) is referred to as the agglomeration effect.

Recent empirical literature finds strong evidence of an agglomeration effect in manufacturing. In sub-sectors of manufacturing, studies demonstrate that agglomeration can reduce production costs (Cohen and Morrison-Paul 2005), increase total factor productivity (Greenstone, Hornbeck, and Moretti 2010), and reduce productivity dispersion among producers (Syverson 2004). In the agricultural setting, a number of studies also find support for an agglomeration effect. For example, Roe, Irwin and Sharp (2001) find that county hog production is positively influenced by hog production in surrounding counties. Their spatial econometric approach to examining the agglomeration effect is similar to Cheng, Gomez, and Bills (2011) who find evidence that sales of greenhouse and nursery products are positively influenced by the sales of greenhouse and nursery products in surrounding areas[1]. Their approach was similar to Isik's (2004) study of agglomeration effects in the U.S. milk production.

With respect to studies of the agricultural sector, our study differs from the above literature in two important ways. First, we measure the effect of agglomeration at the firm level. The heteroscedastic stochastic frontier approach allows us to measure the effect of agglomeration on firm production efficiency and production uncertainty. Second, we use a producer density measure of agglomeration that is not defined by political boundaries (e.g., county) but by densities within a spherical distance of each farm. With respect to

1. The authors find evidence of an agglomeration effect in most geographic regions but not all.

the aforementioned points, our paper is more similar to Tveteras and Battese (2006) who find evidence of agglomeration effects in the Norwegian salmon industry using a stochastic frontier approach. However, unlike Tveteras and Battese (2006), but similar to Syverson (2004), we also examine the agglomeration effect on the variance of production efficiency (or production uncertainty)[2] within a given area. This allows us to assess whether firms in greater proximity to each other are similarly situated on the production frontier.

In the remainder of this paper we describe the model of production that underlies our empirical method for estimating the stochastic frontier. We then review our empirical results. Anticipating this section a bit, we find strong evidence of agglomeration effects in Ontario's dairy sector and some evidence (albeit sensitive to alternative specifications of our density measure) that agglomeration reduces the variance of efficiency. We conclude the paper by discussing the potential implications of our findings for ongoing issues in the agricultural sector.

2. Bera and Sharma (1999: p187) note that the variance of efficiency "...could provide a measure of production uncertainty or risk."

2 Empirical Model

The sharing of ideas by closely located farms is assumed to have a positive external effect on the production efficiency of neighboring farms (i.e., improvement in productive efficiency). Consider a dairy farm uses a vector of inputs, $\mathbf{x} = (x_1, x_2, ..., x_N) \in \Re^N_+$, to produce milk and other products, $\mathbf{y} = (y_1, y_2, ..., y_M) \in \Re^M_+$. We represent the production technology of the farm by input requirement set as $L(y)$={x: x can produce y}. To measure the production efficiency a firm, one can use a variety of approaches: i.e., production function, input and output distance functions, cost function, revenue function or profit function (Kumbhakar and Lovell 2000). For example, the production function defines the maximum possible output that can be produced from a vector of inputs. The cost function defines the minimum cost to produce a given level of output(s). The input distance function describes how far an input vector is from the boundary of the representative input requirement set, given a fixed output. In this paper, we use an input distance function. The key advantage of the input distance function, in our case, is that the Canadian dairy quota regulation restricts the maximum output, with fewer restrictions on the input markets. Further, unlike the cost function, the input distance function does not require input prices to vary among firms (Coelli, Singh and Fleming 2003). The estimation of input distance function assumes that a farm focuses mainly on reducing input usage to produce a fixed amount of output. To operate on the boundary of the production technology, the firm radially scales down the input vectors (Coelli, Rao and Battese 1998; Coelli and Perelman 2000). Kumbhakar et al (2008) and Sipiläinen (2007) used a similar approach to examine Norwegian dairy farms. The input distance function, $d^I(y, x)$, is defined as:

$$d^I(y, x) = Sup_\theta\{\theta : (\frac{x}{\theta}) \in L(y)\} \tag{1}$$

where $d^I(y, x)$ is non-decreasing, linear homogeneous and concave in inputs, and non-increasing and quasi-concave in output (Kumbhakar and Lovell 2000). The input distance function, $d^I(y, x)$, is a measure of technical efficiency. If $d^I(y, x) = 1$, then the input vector lies on the boundary of the input requirement set, and the firm is technically efficient. If $d^I(y, x) > 1$, then the input distance function indicates that the observed input-output vector is technically inefficient. For empirical estimation, θ is defined as a function of farm agglomeration: $\theta_i = g(D)$ where D is the number of neighboring farms (or density) within a given geographical location and distance. In the presence of agglomeration effects we expected that, $\frac{\partial \theta_i}{\partial D} < 0$.

To measure production efficiency both stochastic frontier analysis (SFA) and the non-parametric data envelopment analysis (DEA) are commonly used.[3] The SFA is preferred to DEA for a number of reasons. For example, SFA is less sensitive to outliers (Besstremyannaya 2011), allows modeling firm-specific variables, takes into account stochastic variation due to random noises (Aigner, Lovell and Schmidt 1977), and allows for a statistical hypothesis testing (Hjalmrsson et al 1996). Since it is proposed by Aigner, Lovell and Schmidt (1977) and and Meeusen and van den Broeck (1977), the SFA approach has been extended to examine the determinants of efficiency among firms assuming that inefficiency effects are a function of some firm-specific factors (e.g., Battese and Coelli 1995). For the distance function in equation (1), we can parameterize $\theta = e^u$, where $u \geq 0$ (Das and Kumbhakar 2012). Using the homogeneity property of $d^I(\mathbf{y}, \mathbf{x})$, we can normalize the $n-1$ inputs by the $N-th$ input and describe the distance function as $d^I(\mathbf{y}, \mathbf{x})/x_N = d^I(\mathbf{y}, \bar{\mathbf{x}})$, where $\bar{\mathbf{x}} = x_1/x_N, ..., x_{n-1}/x_N)$. Re-parametrization of θ, i.e., $d^I(\mathbf{y}, \mathbf{x}) = \theta = e^u$, leads to:

$$-\ln(x_N) = \ln d^I(\mathbf{y}, \bar{\mathbf{x}}) - u. \tag{2}$$

3. *A priori* the choice between SFA and DEA entails certain trade-offs (see Hjalmrsson et al 1996 for detailed discussion).

Adding a random error term, ν, to equation (2), a Cobb-Douglas stochastic input distance function with one output is:

$$-\ln(x_{Ni}) = \beta_0 + \sum_{n=1}^{N-1} \beta_n \ln(\frac{x_{ni}}{x_{Ni}}) + \alpha \ln(y_i) + \nu_i - u_i \quad (3)$$

where i represents firms, $-\ln(d_i^I) \equiv \varepsilon_i = \nu_i - u_i$ can be interpreted as a traditional stochastic frontier disturbance term[4]. The distances in a distance function are the radial distances between the observed data points and the frontier that could be due to either a noise (ν_i) or technical inefficiency (u_i). y_i denotes milk output ($i = 1, ...I$); x_i is a $(1 \times n)$ vector of inputs; α and β are unknown parameters to be estimated; ν_i is a two-sided error term with $E[\nu_i] = 0$, $E[\nu_i \nu_j] = 0$ for all i , $i \neq j$; $var[\nu_i] = \sigma_\nu^2$; u_i is a one-sided non-negative error term with $E[u_i] = \mu_i$, $E[u_i u_j] = 0$ for all i, $i \neq j$; $var[u_i] = \sigma_{\upsilon_i}^2$. u_i and ν_i are distributed independently of each other, and the regressors.

One unique contribution to the agglomeration economies literature is that we explicitly model the impact of density on the mean and variance of the inefficiency distribution. If firms located in close proximity to each other are more likely to share knowledge regarding best production practices, then density will be associated with an increase in mean technical efficiency. Moreover, if the sharing of ideas and knowledge leads to a more homogenous production practice, the variance of the efficiency measure is expected to decline. Simply put, the testable hypotheses of the study are that in a more dense areas, the distribution of production efficiency exhibits higher mean and lower variance.

To test for the effect of density on the mean and the variance of production inefficiency effect, we use the heteroscedastic stochastic frontier model (e.g., Caudill, Ford and Gropper 1995). Recent efforts in modeling heteroscedasticity in inefficiency effects (σ_{u_i}) consider a more flexible specification in two ways: 1) Claudill and Ford (1993), Caudill, Ford and Gropper (1995), Hadri (1999) assume μ_i to be constant, but allow the variance

4. Where $u_i = -\ln(TE_i)$

of the inefficiency effect, σ_u^2, to be firm-specific; and 2) Bera and Sharma (1999) and Wang (2002) extend the original conditional variance model to allow for non-monotonic relationship between both $\mu_i = \delta_0 + \mathbf{z}_i\delta$ and $\sigma_{u_i}^2$ and firm-specific factors, $\mathbf{z}$, and specified $\sigma_{u_i} = \exp\{\gamma_0 + \mathbf{z}_i\gamma\}$, where δ and γ are vectors of parameters to be estimated[5]. To estimate equation (3) we regress the negative of the log of feed on the log of milk output, the log of capital input, the log of labor input, the log of other input, year fixed effect, region fixed effect, soil type dummies, breed type dummy, milking technology dummy, feeding technology dummy for the distance function. The mean and variance of the inefficiency effect are expressed as a function of producer density, distance from the nearest urban area, producer's education, producer's age, and herd size. All the parameters of the stochastic distance function are estimated using maximum likelihood approach.

Once the parameters of the model are estimated, the marginal effects of the z-variables on the expected value of the production inefficiency effects, $E(u_i|z_i)$, and the the variance of the inefficiency effect, $Var(u_i|z_i)$, are obtained as follows : $\frac{\partial E(u_i)}{\partial z(ik)}$ and $\frac{\partial Var(u_i)}{\partial z(ik)}$ (see Wang 2002; Wang 2003; and Bera and Sharma 1999 for details), where k indexes the exogenous z-variables. The marginal effects on $E(u_i|z_i)$ and $Var(u_i|z_i)$ measure how an increase or decrease in the exogenous z-variables changes the expected inefficiency (or the log of output) and the production uncertainty, respectively (Bera and Sharma 1999). To obtain the semi-elasticity of the dummy variables, we take the anti-log of the dummy coefficient, subtract 1 from it, and multiply the difference by 100%. Wang (2002, 2003) shows that that two effects of an increase in the exogenous z-variables on mean efficiency are at work: the direct effect that occurs through the increase in mean efficiency and the indirect effect through the the variance. If the variance of inefficiency is homoscedastic, then $\gamma_k = 0$ for all k, and the marginal effect collapses to the direct effect and has the same sign as δ_k for the k^{th} inefficiency effect variable.

5. Jondrow et al. (1982) proposed the conditional mean, $E[u_i|\varepsilon_i]$, as an indicator for technical inefficiency, and Bera and Sharma (1999) proposed the conditional variance, $Var[u_i|\varepsilon_i]$, as a measure of production uncertainty.

The technical efficiency (TE) scores are estimated using the conditional expectation predictor proposed by (Battese and Coelli 1988):

$$T\hat{E}_i = E[(exp(-\hat{u}_i)|\hat{\varepsilon}_i)]. \tag{4}$$

3 Data description and variable definitions

We use four main data sources Data on inputs, output and farm characteristics are obtained from the Ontario Dairy Farm Accounting Project (ODFAP) over the period 2007 and 2008. Data on geographical location of individual farms is obtained from Dairy Farmers of Ontario. Soil class generated using the ESRI software "ArcGIS". Farm distance, from the farm to the nearest urban center, is generated using Geographic Information System (GIS).

The ODFAP sample farms used in this analysis consists of a sample of 104 fluid milk producers in 2007 (84) and 2008 (73) (a total of 157 observations), where 53 of the producers are observed in both years. The data consist of key variables such as capital, labor, feed (concentrate and forage), output, cost, and location. Data for interest rates, inflation rates, corporate income tax rates, tax credit rates, wage rates and producer price indices of some of the inputs are obtained from Statistics Canada (CANSIM). Additional geographic variables - e.g., distance to urbanizing areas - are developed based on geographic information system to account for variation in other location characteristics.

3.1 Production function variables

The input distance function in equation (3) is specified with one output - fluid milk output (hectoliters of 3.6 percent fat content milk)- and four inputs (*x-variables*): 1) *labor*: labor hours used on the farm, measured as total number of hours worked, including family and hired labor; 2) *feed*: the feed input is an aggregate input expenses (deflated by an appropriate price index provided by Statistics Canada) on feed groups such as commercial dairy ration, by-products, brewer grains, protein supplement, salt and minerals, milk replacer, calf ration, hay, silage and other forages; 3) *other*: intermediate inputs include fuel, lubricants, electricity, veterinary services, gasoline and other inputs expenses by the dairy farms, deflated by the CPI to 2002 Canadian dollar prices; and 4) *capital*: the capital input group aggregates services for land and buildings, machinery, and livestock herd capital, deflated by the CPI. In order to isolate differences in production efficiency from heterogeneity in farm technologies and farm environmental characteristics, the distance function includes: 1) dairy regions; 2) milking system; 3) feeding system; 3) animal breed; 4) housing system; 5) yearly dummies; 6) and soil quality.

3.2 Inefficiency effect variables

The inefficiency effect variables, the *z-variables*, consist of the following: 1) dairy farm density, measured as the number of neighboring farms within a certain spherical distance (e.g., 10 kilometers); 2) distance to the nearest urban center, measured in kilometers; 3) farmer's ages, measured in years; 4) farmers' education level, a dummy variable if the farmer has agricultural diploma and higher; and 5) farm size, measured by the number of beginning inventory of cows; 6) natural endowment, measured by soil class for individual farms. The farm density measure, our mesure of agglomeration, requires a more detailed discussion.

One common challenge in examining agglomeration effects is the choice of ideal measure. Some of the measures that are used in the literature include the Hirschman-Herfindahl index of concentration (e.g., Wheaton and Shishido 1981), and the share of population (e.g., Ades and Glaeser 1995). These measures of concentration depend heavily on how a region, a municipal, or a county is defined. Satterthwaite (2007) presents examples of how a metropolitan area can be assigned markedly different population sizes depending on how the political boundary of an area is defined. For the purpose of this study our agglomeration variable is based on the economic significance of a location.

Our measure of agglomeration or density variable uses the spacial coordinates for the entire dairy farms in the province of Ontario. This measure basically counts the number of farms within a certain spherical distance between farms along great circle of the sphere. The spatial coordinates of each dairy farm in the province is collected by Dairy Farmers of Ontario (DFO), which contains longitude and latitude information about all dairy farms in Ontario. We first use the *haversine formula* [6] to compute bilateral distances between all pairs of dairy farms in the province, and then compute the number of neighboring locations within a great circle of 10 kilometers spherical distance.

Our measure of distance "is unbiased with respect to spatial scale and aggregation" (Duranton and Overman 2002; p.5) as it is not based on political boundary (such as county, municipal), but it is based on economic relevance (see for detailed discussion Duranton and Overma, 2002). As in Duranton and Overman (2002), working in a continuous space, our measure directly uses spherical distances between observations to compute density rather than aggregating farms within a political boundary. The use of a political boundary suggests that all farms within a given boundary benefit from other farms in the same boundary - whether the farm is nearby or far away; and do not benefit from nearby firms in the neighboring regions. Unlike Duranton and Overman (2002), who uses Euclidean distance we use a non-Euclidean geometry (i.e., the haversine) to compute bilateral spherical distance between farms to reduce systemic risk due to the curvature of the earth (Duranton and Overman 2002).

One caveat of our density measure is that the choice of what spherical distance to use is a matter of discretion. We do not know *a priori* what exact spherical distance to be used. We must seek this information from the data as the theory does not offer the

6. $Haversine(\frac{d}{R}) = haversine(\varphi_2 - \varphi_1) + Cos(\varphi_1)Cos(\varphi_2) \cdot haversine(\triangle\lambda$ where haversine(θ) = $Sin^2(\theta/2) = (1 - Cos(\theta))/2$, d is the distance between the two points along a great circle of the sphere, R is the radius of the sphere, φ_1 is thee latitude of point 1, φ_2 is the longitude of point 2, $\triangle\lambda$ is the longitude separation, $d = R \cdot haversine^{-1}(h) = 2R \cdot arcsine(sqrt(h)$, $h = haversine(d/R)$. This is implemented using the *distmatch* command in STATA 12. Haversine assumes the earth to be a sphere.

direction as to what spherical distance to use; theory only tells us the mechanism through which producer density affects productive efficiency. For this reason, a robustness check is done with a 5 kilometer spherical distance. Patterns in Figure 1 seems to suggest that farms tend to be drawn to locations where activity in their industry is most concentrated.

Distance to the nearest urban center: We use the distance to the nearest urban location as a measure of access to markets. Historically, because milk is a perishable product, dairy farms locate close to end consumers giving rise to von Thünen-style production rings encircling urban areas where the milk was consumed and priced by distance from the market. In this case, distance may impede the realization of agglomeration benefits. But with improvements in transportation and storage technologies and the increasing urban development into locations traditionally inhibited by dairy farms, milk producers gradually locate their barns in remote areas with lower production costs. Distance by road from the geographical center of the municipality where the farm is located to the boundary of the nearest urban area, as defined by Statistics Canada (2006). Of the 586 municipalities in Ontario, the geographic centroid for 552 municipalities is within 50 km of the nearest road segment that was part of the connected road network (DMTI Spatial, 2005). If the centroid of a municipality is not located on a road segment, the closest road segment to the centre is used. For each municipality there are two important attributes to consider: Snapped distance and Rastervalue. Snapped distance is the distance the centroid is moved ('snapped') to meet the closest road segment. Rastervalue is the distance from the snapped location to the closest urban area. Rastervalue is used as the measure of distance. It is expected that, the distance to the nearest urban area has a positive relationship with the production efficiency of sample dairy farms.

Soil quality: One of the econometric issues in estimating the influence of density on technical efficiency is the possible presence of unobserved factors that raise efficiency and attract more dairy farms to a given location. Agglomeration and its benefits may arise when farms locate in areas with natural cost advantages (Ellison and Glaeser 1999).

For example, locations within a county or a region may differ in terms of land quality. It is possible that more efficient dairy farms are located in areas with a better natural endowments for reasons independent of agglomeration externalities. To resolve this issue and control for the effects of natural endowment on the stochastic distance frontier, we use soil class classification based on the latitude and longitudes of each farm.

The Canada Land Inventory for agriculture capability provides seven classes of soils. Soils descend in quality from Class 1, which is highest, to Class 7 soils which have no agricultural capability for the common field crops. Class 1 soils have no significant limitations in use for crops. Class 2 soils have moderate limitations that reduce the choice of crops, or require moderate conservation practices. Class 3 soils have moderately severe limitations that reduce the choice of crops or require special conservation practices. Class 4 soils have severe limitations that restrict the choice of crops, or require special conservation practices and very careful management, or both. Class 5 soils have very severe limitations that restrict their capability to producing perennial forage crops, and improvement practices are feasible. Class 6 soils are unsuited for cultivation, but are capable of use for unimproved permanent pasture. Class 7 soils have no capability for arable culture or permanent pasture. The soil data for each farm was generated using the ESRI software "ArcGIS". The process of generating this variable required a number of steps. First, a soil map for all of Southeastern Ontario was acquired. This map identifies polygons that represented different soil characteristics. A map layer containing longitude and latitude data for each farm location was created. Soil data for each farm location was then created by combining the two layers of data which connects the characteristics of each relevant polygon with specific firms.

Table 1 shows summary statistics of key variables. It is apparent that there are nontrivial differences in farm output and density. All the estimations in this study are conducted using STATA 12. Note that since the stochastic distance frontier is extremely non-linear and are numerically difficult to converge, some of the variables are scaled before estimation. **TABLE 1 HERE**

4 Results

Table 2 provides the maximum likelihood parameter estimates of the Cobb-Douglas stochastic input distance frontier, and the mean and variance of inefficiency effects[7]. As discussed earlier, for identification purposes, homogeneity of degree one in inputs is imposed on the the input distance function before estimation.

TABLE 2 HERE

We estimate two alternative models: one with both mean and variance effects (Model 1), which incorporates the z-variables into both mean and variance of production inefficiency distribution; and one with mean production inefficiency effect only (Model 2). Model 2 excludes the z-variables from the efficiency variance effect. In Table 2, column [2] shows parameter estimates and t-values of the parameters for Model 1, whereas column [3] provides the parameter estimates and t-values for Model 2. A likelihood ratio is used to test the hypothesis that the model with mean efficiency effect is not different from the model with mean and variance of inefficiency effects. The test statistic for the likelihood ratio (LR) test is 25.45. The 5 percent chi-square critical value with 5 degrees of freedom is 11.07, thus we reject the null hypothesis, and hence, the unrestricted model with mean and variance inefficiency effect is preferred. Hence, we discuss our results in reference to the unrestricted model, Model 1.

The findings in Table 2 identify the effect of milk output and the inputs on distance function. A negative sign for output is associated with lower distance whereas a positive sign for inputs is associated with greater distance. In terms of individual coefficients, the coefficient for milk output is negative and statistically significant at the 5 percent significance level, meaning that as the level of output increases the input "distance"

7. One concern with the Cobb-Douglas functional form is that it may impose unwarranted restrictions upon the production technology. To address this concern a translog input distance function is estimated. Based on Likelihood ratio (LR) test we fail to accept the translog model (Log-likelihood function = 82.18) in favour of the Cobb-Douglas model (Log-likelihood function=77.67) (LR=9.02; chi-square(5 percent), for 10 degrees of freedom is 18.31). The Cobb-Douglas form is appropriate for the sample data used in the paper, but it is unlikely to be the case for all data sets, and we conclude that the extra complexity of the translog is not warranted in this study

decreases. The coefficient of milk output is less than one in absolute value, indicating that the industry exhibits increasing returns to scale. The standard returns to scale elasticity, which is regularly reported in production function studies, is equal to the inverse of the negative of the coefficient of output for input distance function (i.e., RTS $= -1/\alpha =$ 1/0.69=1.4) (Coelli, Singh and Fleming 2003). Based on LR test the constant returns to scale hypothesis is rejected at the one percent significance level. This finding is consistent with Moschini's (1988) finding of increasing returns to scale for Ontario dairy farms with larger levels of milk production but decreasing returns to scale for very largest ones. For the U.S. dairy farms, Tauer and Mishra (2006) also find increasing returns to scale. The increasing returns to scale finding may explain why the average herd size has been increasing over time in Ontario, for example, from approximately 54 cows per farm in 2000 to 74 cows per farm in 2010. The coefficients for inputs are positive and have statistically significant influence on the "stochastic distance frontier". In examining agglomeration effects we believe it is important to control for differences in natural endowments. Natural endowment advantages may explain variation in technology (i.e., distance function). We include two measures of natural endowments in our estimation of the distance function - i.e., soil quality and regional variables. Soil quality and regional differences may explain underlying differences in the chosen technology.

We included three dummy variables for prime agricultural areas- i.e., Class 1, Class 2 and Class 3 soils (Class 4-7 are reference group). The coefficients for soil classes are statistically insignificant. While this result would seem counterintuitive for some farm types - i.e., row crops - land quality may be less significant for dairy production[8]. Moreover, a closer examination of Table 1 shows that ninety percent of the sample dairy farmers operate on prime agricultural lands. The regional coefficient for the categorical variable that identifies firms in southern-eastern Ontario region is statistically significant suggesting that producers in this region are on a higher frontier relative to producers in

8. Herath, Weersink and Carpetier (2004) indicate that advances in facilities technology, irrigation, and management practices have minimized constraints and dependence on locally grown feedstuffs.

southern-western Ontario (the reference group). None of the technology variables did not have effect on the distance function; i.e., the coefficients on milking system, cow breed, and feeding system are statistically insignificant.

Table 2 also describes the effect of producer density and other variables on the mean and variance of the distribution of the production inefficiency effect. For both models 1 and 2, producer density has a negative effect on the mean inefficiency effect, indicating that a farm in a more dense area has a higher mean production efficiency. For the model with mean and variance effects, farm density has a negative and statistically significant effect on the variance of production inefficiency, suggesting that the variance of production inefficiency are likely lower in locations with a higher producer density. In the results presented in the inefficiency effects portion of Table 2, most of the other z-variables are statistically significant.

Table 3 reports the marginal effects of the z-variables on the mean and variance of inefficiency effects. The marginal effects display a monotonic non-linear relationship between producer density and the mean inefficiency effects. The absolute magnitude of the negative effect at a lower quartile is higher than for those at a higher density-quartile. The average marginal effect in the first density-quartile is -0.00636. Since $\partial E(-\ln(d^I_{ij}))/\partial density = -\partial E(u)/\partial density$, for a unit increase in producer density, the marginal effect translates into a decrease in the inputs vector by 0.636 percent to produce the current level of output, holding the current mix of inputs constant. The effect for the fourth density-quartile is -0.0024, suggesting a decrease in the input vector by 0.24 percent. To illustrate the economic significance of the marginal effects, take for example, the average labor hours for the first density-quartile is approximately 7,164 hours per year in 2008 and the 0.636 percent reduction translates to about 45.56 labor-hour savings per year per farm (a saving in a range of C$455- C$774), all other things being constant. But if we do not allow density to influence the variance, the marginal effect for the first density-quartile is -0.00119, meaning a decrease in the inputs vector by 0.119% which translates to about 8.5 labor-hour savings per year per farm (a saving in a range of C$85-C$145).

TABLE 3 HERE

Panel B of Table 3 presents the marginal effects of the z-variables on the variance (i.e., production uncertainty) of the inefficiency effect, $\partial V(u)/\partial z$. Producer density has a statistically significant negative effect for the first three quartiles, meaning that density reduces production uncertainty. But the magnitude of the marginal effect is larger for farmer in the first density-quartile, suggesting a non-linear effect of density on production uncertainty and that farmers in less dense areas may benefit more from an increase in density. Notice that the sign of the marginal effect of the mean and variance of the inefficiency effect are the same. This may suggest that as farms attempt to move towards their frontier they not only reduces the level of inefficiency, but they also reduce their production uncertainty. Batra and Ullah (1974) noted that a marginal decrease in uncertainty stimulates an increase in the firm's output, provided the absolute risk aversion is decreasing.

The estimated potential agglomeration externalities effects on the distribution of productivity may vary with the spatial scale. We conduct a sensitivity analysis with regards to the spherical distance chosen. As we mentioned earlier in the data section, the choice of what spherical distance to use is a matter of discretion. Recent works on agglomeration in cities provide evidence that agglomeration economies take place over a remarkable short distances suggesting that face-to-face contact and interaction with nearby colleagues is an important element in the overall advantages of cities (Rosenthal and Strange 2003; Fu 2007; Arzaghi and Henderson 2008). Some studies find strong agglomeration benefits of knowledge spillovers (e.g., Baldwin et al. 2008; Graham 2009; Aharonson et al. 2007); Hoogstra and van Dijk 2004) within within 5-10 km. To explore these issues, we created a measure of agglomeration at 5 kilometers spherical distance, and re-estimated the stochastic distance function. Again, we estimated two separate models: the inefficiency effect model (Model 1), and the inefficiency and variance effects model (Model 2). Table 4 shows the results of 5-km spherical distance model; and Table 5 shows the marginal effects of the 5-kilometer model. Comparison of Tables 2 and 3 suggests that density at 10 kilometers has a much greater influence on the mean inefficiency effects than density at 5 kilometers; the marginal effect of mean inefficiency effect with respect to density is -0.003111 for 10 kilometers and -0.001911 for 5 kilometers (Table 5). It is important to note that the average marginal effects with respect 5 kilometers density is lower than the 10 kilometers density. This is mainly because the coefficient for the variance effect is lower (in absolute value) and statistically insignificant for 5 kilometers than the 10 kilometers model.

TABLE 4 HERE

TABLE 5 HERE

5 Concluding remarks

We find that Ontario dairy farms situated in areas characterized by high dairy farm density are more efficient than a similar dairy farm located in areas of low dairy farm density. Moreover, we find some evidence that Ontario dairy farms located in high density areas are more similar, with respect to efficiency measures, than dairy farms located in areas that are less concentrated with respect to dairy production. Over simplifying the matter a bit, being near more farmers appears to make a farmer more productive and more like his or her neighbors. This finding supports the agglomeration hypothesis; the exchange of productivity-enhancing information appears to be enhanced by proximity and density to similar firms that become more similar as a result of this information exchange.

Our findings may support an enhanced understanding of a number of potentially related phenomena in the agricultural sector. For example, the supply of agricultural land is relatively inelastic, hence increases in demand for land in areas of high firm concentration (because of the agglomeration effect) may result in relatively higher land values. Future hedonic studies may want to control for farm density in assessing farmland values. Given our findings we expect this effect in the dairy sector but it remains an important area of future research to assess the agglomeration effect for other farm types: e.g., dairy, cattle, grains.

More generally, our findings may be useful in understanding Henneberry and Barrows (1990) observation that exclusive agricultural zoning was observed in some regions of Wisconsin that were politically dominated by farmers. Farmers may implicitly recognize agglomeration effects - i.e., the efficiency benefits of being around other farmers - and actively seek to ensure the permanence of farming in their areas. If agglomeration effects differ amongst farm types then future studies might expect farmer led zoning efforts to be more pronounced in these areas.

From an outreach perspective, our results confirm a longstanding justification for agricultural extension efforts throughout the United States, information matters. But the agglomeration effect suggests that the information content is enhanced (from a productivity standpoint) when passed by greater numbers of similar situated farmers in close proximity. Understanding the reasons for this enhancing and seeking ways to emulate the agglomeration effect (perhaps through new innovative forms of social media) is an area for future research and extension collaboration.

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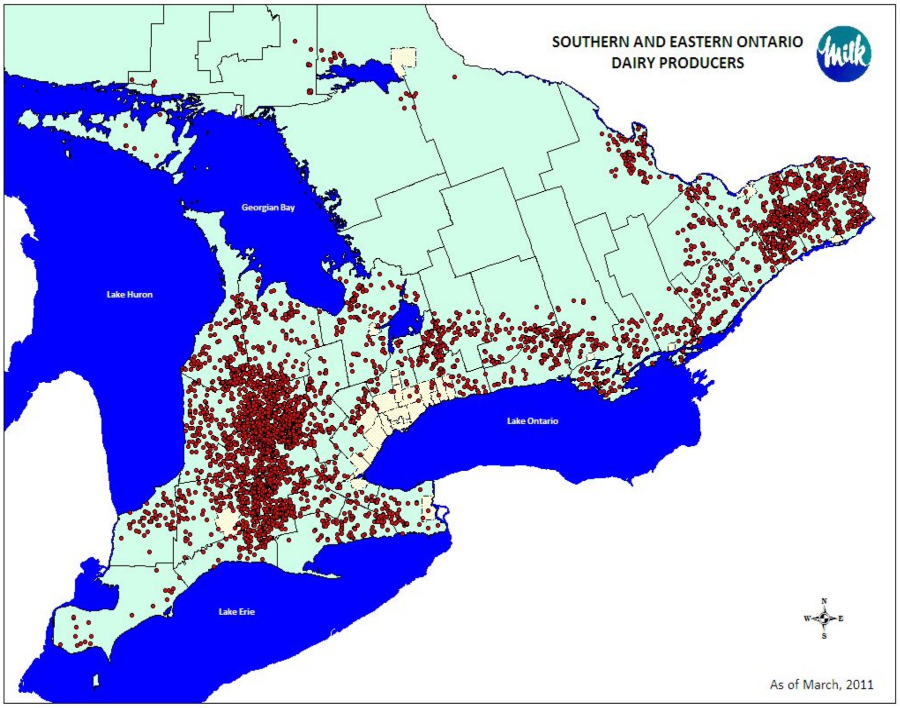

Figure 1: Distribution of Southern and Eastern Ontario Dairy Producers

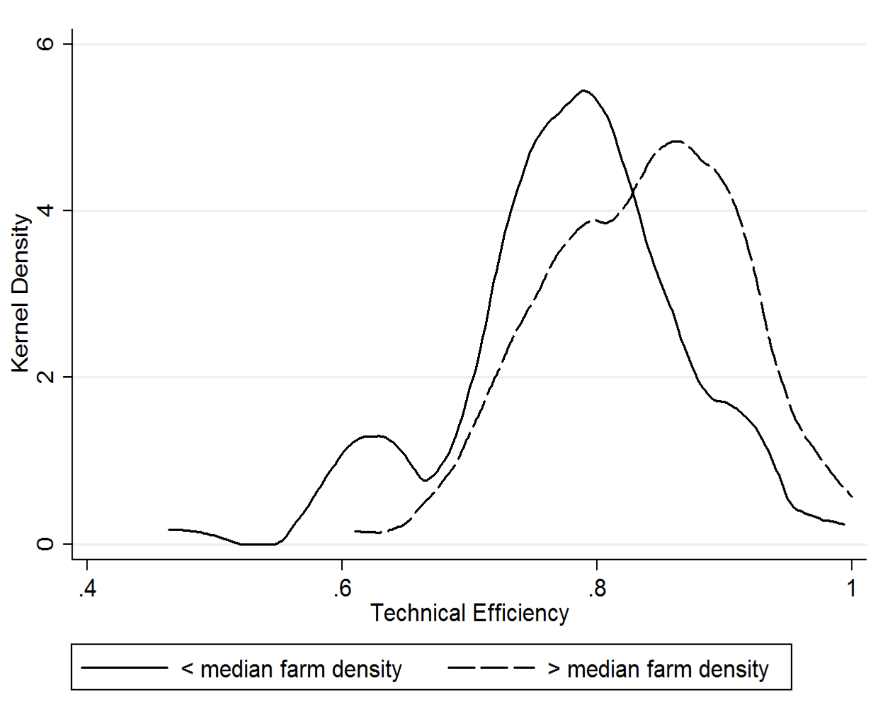

Figure 2: Technical Efficiency density estimates, farms in areas below and above median farm density

Table 1: Summary Statistics: Means and Standard Deviations

		2007		2008	
Variables	Unit	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Milk	Hectoliter	7116	5703	6773	(5299
Feed	C$	106925	83552	113014	83256
Labor	Hours	6776	2755	6781	2527
Capital	C$	74300	64367	74678	53808
Other	C$	45012	35361	42175	27803
Milking system-parlour	0/1	0.357	0.482	0.342	0.478
Feeding system-fully automated	0/1	0.262	0.442	0.247	0.434
Breed-Holstein	0/1	0.952	0.214	0.918	0.277
Class 1 Soil	0/1	0.381	0.489	0.356	0.482
Class 2 Soil	0/1	0.345	0.478	0.315	0.468
Class 3 Soil	0/1	0.155	0.364	0.164	0.373
Class 4 Soil	0/1	0.048	0.214	0.055	0.229
Class 5 Soil	0/1	0.012	0.109	0.055	0.229
Class 6 Soil	0/1	0.024	0.153	0.027	0.164
Class 7 Soil	0/1	0.036	0.187	0.027	0.164
South-western	0/1	0.381	0.489	0.370	0.486
South-central	0/1	0.298	0.460	0.370	0.486
South-eastern	0/1	0.321	0.470	0.260	0.442
Density 10-km	Number	48.143	42.818	45.164	44.060
Density 5-km	Number	13.726	12.773	13.014	12.807
Distance from Urban	kilometers	6.726	6.929	6.753	7.120
Education	0/1	0.595	0.494	0.603	0.493
Farmer's Age	Years	46.976	8.916	47.425	9.246
Herd Size	Cows	75.202	53.392	74.356	49.907
Number of producers		84		73	

Table 2: Maximum Likelihood Parameter Estimates for the Distance Frontier and the Determinants of Inefficiency for 10K Density Models

	(Model 1) Inefficiency & Uncertainty		(Model 2) Inefficiency only	
	Stochastic Distance Function			
Log of Milk	-0.696***	(-14.42)	-0.691***	(-12.93)
Log of Others	0.301***	(6.17)	0.328***	(6.60)
Log of Capital	0.0364	(1.63)	0.0281	(1.25)
Log of Labour	0.187***	(4.75)	0.204***	(5.27)
Year:2008	-0.0610**	(-2.57)	-0.0537**	(-2.10)
South-central Ontario	-0.0275	(-0.88)	-0.0539*	(-1.72)
South-Eastern Ontario	-0.102***	(-2.95)	-0.114***	(-2.93)
Parlour Milking System	0.0189	(0.49)	0.0207	(0.51)
Automated Feeding	-0.00166	(-0.04)	0.00656	(0.16)
Holstein Breed	0.0820	(1.49)	0.0461	(0.89)
Class 1 Soil	0.0102	(0.25)	0.0258	(0.63)
Class 2 Soil	-0.00145	(-0.03)	0.00669	(0.13)
Class 3 Soil	0.0441	(0.89)	0.0587	(1.23)
Constant	-4.413***	(-11.06)	-4.362***	(-10.30)
	Mean inefficiency Effects, $E(u_i\|z_i))$			
Density:10KM	-0.000639*	(-1.90)	-0.00119***	(-3.67)
Distance from Urban	-0.00482***	(-2.70)	-0.00620***	(-3.13)
Education	-0.0130	(-0.45)	-0.0338	(-0.97)
Farmers' Age	0.00756***	(4.80)	0.00437***	(2.78)
Herd Size	0.00112**	(2.03)	0.000950*	(1.81)
Constant	-0.170	(-1.32)	0.0582	(0.60)
	Variance inefficiency Effects, $Var(u_i\|z_i))$			
Density:10KM	-0.182**	(-2.16)		
Distance from Urban	-0.520*	(-1.75)		
Education	-6.412**	(-2.23)		
Farmers' Age	-0.526***	(-2.77)		
Herd Size	0.00909	(0.87)		
Constant	25.79**	(2.32)	-10.16***	(-5.77)
$\ln(\sigma_v)$	-3.964***	(-32.92)	-3.667***	(-30.06)
N	157		157	
Log-likelihood function	77.676		64.953	
Mean technical efficiency(%)	81	[78, 84]	81	[80, 82]

t statistics in parentheses; Asterisks denote statistical significance:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: The average marginal effects of the z-variables on production inefficiency $E(u_i)$ and production uncertainty $Var(u_i)$ for the 10km model

	Panel A: Production Inefficiency Effects by Quartiles, $\frac{\partial E(u_i)}{\partial z(ik)}$				
	Mean	1st	2nd	3rd	4th
Density $\times 10^2$	-0.3111***	-0.6355***	-0.3055***	-0.0639***	-0.2356
	(-4.62)	(-3.29)	(-3.06)	(-25000)	(-2.46)
Urban $\times 10^2$	-1.1661***	-1.8143***	-1.0202***	-0.5822***	-0.8942***
	(-6.18)	(-3.69)	(-4.12)	(-7.76)	(-4.44)
	Panel B: Production Uncertainty Effects by Quartiles, $\frac{\partial Var(u_i)}{\partial z(ik)}$				
	Mean	1st	2nd	3rd	4th
Density $\times 10^2$	-0.1115**	-0.2982**	-0.0907**	-0.0008**	-0.0529**
	(-2.48)	(-1.98)	(-2.44)	(-1.75)	(-1.56)
Urban $\times 10^2$	-0.3210**	-0.7391**	-0.1823**	-0.0599*	-0.1374
	(-2.49)	(-1.97)	(-2.11)	(-2.13)	(-2.09)

t statistics in parentheses based on Bootstrap standard errors with 1000 replications.
Asterisks denote statistical significance:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Maximum Likelihood Parameter Estimates for the Distance Frontier and the Determinants of Inefficiency for 5K Density Models

	(Model 1) Inefficiency & Uncertainty		(Model 2) Inefficiency only	
	Stochastic Distance Function			
Log of Milk	-0.701***	(-13.91)	-0.697***	(-12.07)
Log of Others	0.311***	(6.44)	0.331***	(6.56)
Log of Capital	0.0400*	(1.85)	0.0294	(1.29)
Log of Labour	0.199***	(4.96)	0.201***	(5.06)
Year:2008	-0.0580**	(-2.38)	-0.0573**	(-2.25)
South-central Ontario	-0.0468	(-1.36)	-0.0597*	(-1.79)
South-Eastern Ontario	-0.116***	(-3.14)	-0.128***	(-2.92)
Parlour Milking System	0.00994	(0.26)	0.0153	(0.38)
Automated Feeding	-0.00111	(-0.03)	0.00655	(0.15)
Holstein Breed	0.0764	(1.37)	0.0490	(0.88)
Class 1 Soil	0.00703	(0.17)	0.00597	(0.14)
Class 2 Soil	0.00347	(0.08)	-0.0122	(-0.24)
Class 3 Soil	0.0360	(0.74)	0.0360	(0.74)
Constant	-4.313***	(-10.52)	-4.303***	(-9.13)
	Mean inefficiency Effects, $E(u_i\|z_i))$			
Density:5KM	-0.00221**	(-2.24)	-0.00373*	(-1.82)
Distance from Urban	-0.00427**	(-2.49)	-0.00659	(-1.56)
Education	-0.00632	(-0.22)	-0.0318	(-0.63)
Farmers' Age	0.00664***	(4.03)	0.00452***	(2.62)
Herd Size	0.000953*	(1.81)	0.000932*	(1.68)
Constant	-0.117	(-1.07)	0.0325	(0.20)
	Variance inefficiency Effects, $Var(u_i\|z_i))$			
Density:5KM	0.0112	(0.15)		
Distance from Urban	-2.001*	(-1.67)		
Education	-3.641*	(-1.70)		
Farmers' Age	-0.466*	(-1.69)		
Herd Size	-0.00364	(-0.27)		
Constant	18.76	(1.55)	-5.778**	(-2.00)
$\ln(\sigma_v)$	-3.889***	(-37.45)	-3.761***	(-11.01)
N	157		157	
Log-likelihood function	73.329		63.013	
Mean technical efficiency(%)	81	[78, 83]	82	[73, 90]

t statistics in parentheses; Asterisks denote statistical significance:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: The average marginal effects of the z-variables on production inefficiency $E(u_i)$ and production uncertainty $Var(u_i)$ for the 5km model

	Panel A: Production Inefficiency Effects by Quartiles, $\frac{\partial E(u_i)}{\partial z(ik)}$, Model 1				
	Mean	1st	2nd	3rd	4th
Density $\times 10^2$	-0.1911***	-0.2048***	-0.1919***	-0.1651***	-0.2045***
	(-16.96)	(-17.34)	(-14.97)	(-4.45)	(-34.88)
Urban $\times 10^2$	-3.7884**	-10.8181*	-1.2141***	-0.4271	-0.4271
	(-2.17)	(-1.89)	(-2.64)		
	Panel B: Production Uncertainty Effects by Quartiles, $\frac{\partial Var(u_i)}{\partial z(ik)}$, Model 1				
	Mean	1st	2nd	3rd	4th
Density $\times 10^2$	0.0300	0.0062	0.0025*	0.1062	0.0002
	(1.10)	(1.09)	(1.82)	(1.08)	(1.16)
Urban $\times 10^2$	-5.8363	-19.3193	-0.1659	-2.12E-06***	-1.51E-06*
	(-1.15)	(-1.13)	(-1.71)	(-3.17)	(-1.81)

t statistics in parentheses based on Bootstrap standard errors with 1000 replications.

Asterisks denote statistical significance:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.