Scale Economies, Technical Efficiency, and the Sources of Total Factor Productivity Growth of Quebec Dairy Farms

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Canada's average cost for milk production is among the highest in the world. This paper focuses on specific potential causes by estimating economies of scale and technical efficiency for a panel of Quebec dairy farms that spans the 2001–10 period. Additionally, this paper investigates the sources of total factor productivity growth. The stochastic frontier analysis, based on an input-distance function, is used to estimate returns to scale relationships across dairy farms. The results show that there is significant economies scale to be exploited and that cost of production could also be reduced by improving technical efficiency. Accordingly, the paper indicates that input-mix effect is the main source of total factor productivity growth. The results have important implications for Canada's supply management policy, and more specifically for the trading of production quota between dairy farmers, as well as for the delivery of targeted extension services.

Les coûts de production du lait au Canada sont parmi les plus élevés du monde. Cette étude cible deux causes potentielles, les économies d'échelle et l'efficience technique en utilisant des données de panel de fermes laitières québécoises couvrant la période 2001–2010. L'étude s'est aussi intéressée aux sources de la croissance de la productivité totale. La fonction de distance orientée sur les intrants a été utilisée pour dériver une frontière stochastique et évaluer l'élasticité d'échelle entre les producteurs laitiers. Les résultats indiquent qu'il y a d'importantes économies d'échelle à exploiter et que les coûts de production pourraient également être réduits en améliorant l'efficience technique. De même, les résultats montrent que l'effet provenant de la combinaison des inputs constituent la principale source de la croissance de la productivité totale. Les résultats ont des implications importantes en ce qui a trait à la politique de gestion de l'offre et plus spécifiquement pour les règles sur les échanges de quotas de production, de même que pour l'offre de services ciblés de vulgarisation.

> *« Les histoires d'économie d'échelle, c'est vrai dans une usine, mais pas en agriculture . . . sur le plancher des vaches, il y a peu d'arguments économiques pour justifier les grosses entreprises agricoles » (La Terre de Chez Nous* 2012*).*

INTRODUCTION

The dairy sector is the third most important farming sector in Canada in terms of farm cash receipts, after grains and oilseeds and red meats (Canadian Dairy Information

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Centre 2014). The dairy industry is concentrated in the central region of Canada, namely Quebec and Ontario as 81.5% of Canada's dairy farms and 68% of federally registered and provincially licensed dairy processors are located in these two provinces. Canada's dairy processing is dominated by three firms: Saputo, a multinational firm based in Montreal; Agropur, a large Quebec-based cooperative with plants across Canada, the United States, and South America; and Lactalis, one of France's largest multinational firm which acquired Parmalat in 2011. Canadian cheese makers are recognized internationally for the quality of their products and the number of different Canadian cheeses has grown rapidly in the last decade, with 1,050 different entries listed in the *répertoire des fromages canadiens*. Saputo and Agropur have made major acquisitions in the United States, Europe, South America, and Australia to penetrate foreign markets which signal that they are competitive on the world scene.

Unfortunately, the competitiveness of Canada's dairy industry is hindered by some of the world's highest milk production costs. According to International Farm Comparison Network (IFCN; 2012, p. 22), Canada is the third highest cost country, after Switzerland and Finland, with cost of production around 75 U.S.$ per 100 kg milk. In 2011, leading farms in Western Europe had costs in the range of 40–50 U.S.$, while costs of 30–35 U.S.$ and \$37 were observed for farms in Oceania and the United States, respectively. One implication is that Canada is also among the top countries for farm-gate and consumer milk prices (IFCN 2012, pp. 26, 59).[1] Another implication is that Canadian processors have exploited opportunities in foreign markets through foreign direct investment instead of through exports. Whether the current policy environment will be the same in 10 years or not, lower milk production costs could generate tangible benefits and as such it is most pertinent to investigate the performance of dairy farms.

The performance of dairy farms in terms of technical, allocative, scale, input-mix, and environmental efficiencies has been the object of many studies in the United States and Europe. For example, Fernandez et al (2002, 2005) estimated an input-distance function with good (e.g., milk production) and bad (e.g., pollutants) outputs and showed that there is much variation in technical efficiency among Dutch dairy farms and that technical efficiency scores are positively correlated with environmental efficiency scores. They also found evidence of increasing returns in the production of good outputs and decreasing returns in the production of bad outputs. Rasmussen (2010) compared the crop sector, the pig sector, and the dairy sector in Denmark in terms of technical efficiency and output scale efficiency. They found that dairy farms operate at a high degree of technical efficiency. Interestingly, Danish dairy farms did not get closer to the efficient output scale between 1985 and 2000 even though the average herd size increased from 35 to 62 cows. However, they began to get closer to the efficient scale between 2000 and 2006 as the average herd size increased from 62 to 97.

Historically, the issues of returns to scale and technical efficiency in dairy production have attracted much attention in the United States because of the wide range of observed herd sizes. Kumbhakar et al (1991) found that large farms operated by producers with a higher level of education tend to be more efficient, technically and allocatively. Even though they did not find evidence of increasing returns to scale, they found that larger

[1] The IFCN produces an annual report based on statistics provided by dairy economists from various countries. Dairy Farmers of Canada is a participating institution.

farms had lower returns to scale than smaller ones and this along with their results on efficiency prompted them to predict that the number of larger farms would continue to grow over time. This prediction turned out to be right according to Mosheim and Lovell (2009) who show that the contribution of dairy farms with less than 200 cows to the U.S. dairy herd fell from about 60% in 1998 to 34% in 2007 while that of the farms with at least 2,000 cows increased from 7% to 23%. This latter study applied a shadow cost model to assess the relative importance of scale effects, technical efficiency, and allocative efficiency in explaining variations in costs of production across farms. They too found that large farms are more efficient than smaller ones. However, their results clearly show that the main driver behind the consolidation in the U.S. dairy sector is scale economies. Interestingly, their model shows that diseconomies of scale eventually occur as the herd size reaches a certain threshold, but even the largest farms in their sample with herd sizes in excess of 2,000 cows were falling short of that threshold.

In contrast, Tauer and Mishra (2006) found that the higher cost of production for many smaller dairy farms in United States is caused by inefficiency. Others have focused on the relationship between technical efficiency and farm size, like Haghiri et al (2004) who found no correlation between farm size and the level of estimated technical efficiency for Ontario and New York dairy farms.

There have not been many studies focusing on scale economies in the Canadian dairy industry. Most are now dated and none pertain to Quebec's dairy industry even though Quebec is the largest milk producing province. Moschini (1988) investigated the cost structure of Ontario dairy farms using a multiproduct cost function approach and found evidence of economies of scale for most output levels, except for the largest 15% of the farms in his sample for which he found constant returns. It was also reported that the farm price was set at a high enough level to cover the production costs of virtually all but the most scale inefficient producers. Hailu et al (2005) investigated cost efficiency for Alberta and Ontario dairy farms using a pooled data covering the 1984–96 period. They report a high average cost efficiency score of 89% and that Ontario dairy farms are relatively more cost efficient. Their results also show that the smallest dairy farms (less than 25 cows) in Ontario were the least cost efficient while farms in this category were the most cost efficient in Alberta.

Weersink et al (1990) decomposed technical efficiency of Ontario dairy farms in terms of pure technical efficiency, input congestion, and scale efficiency components. They found that 43% were 100% overall and scale efficient and that 54% were 100% scale efficient. Their mean efficiency scores were very high: 92% for overall technical efficiency and 96% for scale efficiency. Herds with more than 50 cows had higher overall technical efficiency scores. Technical efficiency results reported in Yélou et al (2010) and Mbaga et al (2003) for Quebec dairy farms are also very high,[2] but these studies did not address economies of size.

[2] The mean technical efficiency levels reported in Ontario and Quebec studies (Weersink et al 1990; Mbaga et al 2003; Yélou et al 2010) exceed Jaforullah and Whiteman's (1999) estimate of 0.89 for New Zealand dairy farms, Fernandez et al's (2005) estimate of 0.68 for Dutch dairy farms, Hallam and Machado's (1996) 0.6–0.7 estimates for Portuguese dairy farms, and Mosheim and Lovell's (2009) estimate of 0.75 for U.S. dairy farms. A high mean technical efficiency level simply means that performance is rather homogenous across farms in the sample. The distribution of Ontario and Quebec dairy farms by size is highly skewed toward small farms that have benefited from stable

The objective of this study is twofold. First, the primary objective of the paper is to shed some light on the existence and magnitude of scale effects for Quebec dairy farms while taking into account differences in technical efficiency across farms. Because the data have a temporal dimension, the evolution of scale and technical efficiencies can be characterized over time. Second, the paper further investigates whether there is any relationship between scale efficiency, technical efficiency, and key farm characteristics and how important the changes in scale efficiency are compared with other components of total productivity change. The results of this study support the existence of increasing returns to scale on Quebec dairy farms, in contradiction with the quota at the beginning of the paper. Though lower than in previous Quebec studies, the average level of technical efficiency is high. Thus, the results suggest that Quebec dairy farmers are efficient managers, but that they could secure cost of production reductions through increases in the scale of their operation. The input-mix effect (IME) is the main source of productivity change, indicating that the composition of input is more important in dairy farms performance growth than technical change (TC). The results have important policy implications, particularly for the regulations about the pricing and trading of production quotas.

The remainder of the article is structured as follows. The next section presents some statistics about farm size in Quebec and in other Canadian provinces and discusses why the sort of structural change observed in the United States has not taken place in Canada. The "Model Specification" section focuses on methodology and, more specifically, on the stochastic input-distance frontier function and performance measures associated with it such as the elasticity of scale (EOS) and technical efficiency scores. This section also includes the Malmquist productivity index and a decomposition of input-oriented Malmquist index computed from the parameter estimates of a translog input-distance function. The data description is included in the "Data" section. The estimation results are then presented along with a discussion about the policy implications which entail making significant changes in the manner Canada's supply management policy is administered. The last section summarizes the results and policy implications.

DAIRY HERD SIZE AND SUPPLY MANAGEMENT

In Canada and in the United States, the number of dairy farms has decreased over time, as the production of milk per cow increased. Macdonald et al (2007) report that there were 648,000 dairy farms in the United States in 1970 and only 75,000 were left by 2006. All herd size categories under 500 cows declined significantly between 2000 and 2006 while the number of herds with 1,000–1,999 cows and over 2,000 cows increased by 25.2% and 104.6%, respectively. The average herd in the United States is 183 cows, but it varies across states with some states having an average herd size in excess of 1,000 cows.[3]

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prices that systematically adjust when input costs increase. Dairy producers in other countries face lower and more volatile prices and this might explain why average technical efficiency is not as high as in Canada. Hadley et al (2013) also argue that farmers may not be able to make state-contingent adjustments, thus operating over extended periods with the wrong input mix and the wrong input quantities.

[3] In 2013, the average herd in Missouri had 64 cows while the average herd in California had 1,030 cows (USDA 2014). Generally, farms in western and southern states have large herds while farms

Table 1. Number of dairy farms by herd size by province

Province	Total farms	Ave. herd size	Herd size groups (dairy cows)					
			<50	50–99	100–149	150–199	200–499	>500
CDA	12,207	79	5,071	4,890	1,297	396	494	59
NFLD	36	182	6	8	9	3	8	2
PEI	189	74	83	75	21	3	7	–
NS	257	97	85	104	36	18	13	1
NB	228	90	76	88	39	12	12	1
QC	5,915	59	2,916	2,470	364	92	68	5
ON	4,036	80	1,581	1,655	491	129	162	18
MN	333	135	79	126	67	21	30	10
SASK	141	165	24	41	30	16	26	4
AB	485	141	70	150	118	64	78	5
BC	587	153	151	173	122	38	90	13

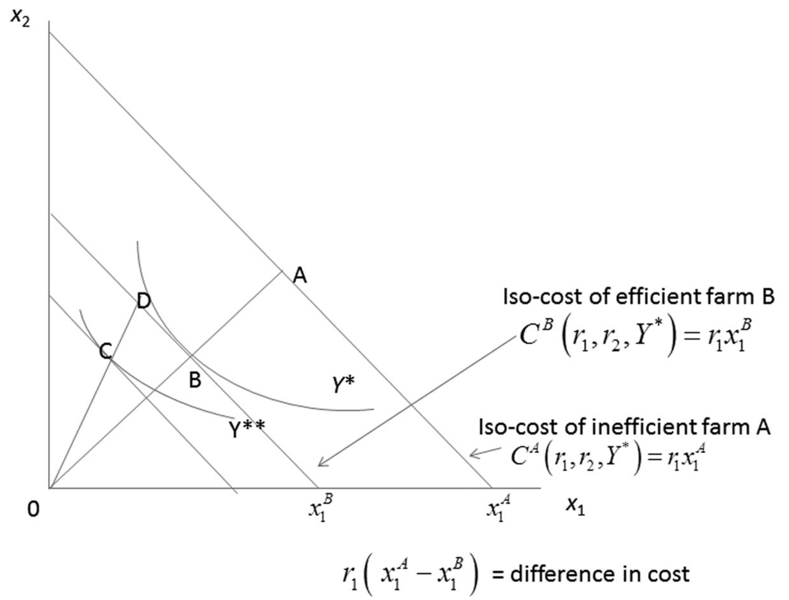
Sources: Data from the 2011 Census of Agriculture, except average herd size which was computed as the ratio of the number of cows and dairy farms by province from the Canadian Dairy Information Center (2014) statistics.

In Canada, there were 122,914 dairy farms in 1970, compared to 14,660 in 2006 (Canadian Dairy Information Center 2014). Thus, the rate of decline (i.e., 88%) is the same as for the United States even though the two countries have relied on different dairy policies. The Canadian dairy industry has been governed by a supply management system while the U.S. dairy sector has transitioned from a centralized market chain with much government intervention to a more commercialized and market-oriented industry (Haghiri et al 2004).

Average dairy herd sizes across provinces show less dispersion than across the U.S. states and the fraction of farms with 500 cows or more is also much smaller than in the United States. In all provinces, the most important size category is 50–99 except in Quebec where farms with less than 50 cows dominate, as shown in Table 1. Clearly, the much-discussed trend toward very large dairy farms observed in the United States has yet to begin in Canada. In the United States, cost reduction is the main reason for the increase in the number of very large farms. Production costs are influenced by several factors and perhaps Canada's harsher climate or environmental constraints make it more difficult to exploit economies of size. This would mean that the extent of the economies of scale reported in Mosheim and Lovell (2009) could not be replicated in Canada. On the other hand, if there are economies of scale to be exploited in Canada, the policy and regulatory impediments that prevent individual dairy farms from expanding could be mining the competitiveness of Canada's dairy industry.

Dairy production quotas are traded to encourage the reallocation of production capacity from low to high productivity farms. If the relationship between herd size and average cost of production in Canada is somewhat close to that observed in the United

in the northern states have smaller herds. USDA production cost estimates for farms with 50–99 cows are twice as large as those for farms with over 1,000 cows.



Notes: The cost differential to produce Y* units of output between technically and allocatively efficient farm B and technically inefficient farm A, whose efficiency level is OB/OA , is $r_1(x_1^A - x_1^B)$, with x_1^A and x_1^B denoting the quantities of input 1 used by farms A and B and r_1 is the price of input 1. If an x_1-saving technology or a change in input quality shifts the isoquant from Y^* to Y^{**} and the input combination remains at B, an input-mix inefficiency effect CD/OC arises.

Figure 1. Technical efficiency and cost of production

States, Canadian dairy herds would have to undergo dramatic increases to be competitive cost-wise. Even under decreasing returns, welfare gains can be presented by allowing more technically efficient producers to purchase quota from less efficient ones. The concept of technical efficiency is illustrated in Figure 1 where farm B requires less inputs than farm A to produce the same level of output/production quota Y^*. Assuming that both farms are allocatively efficient by equating their marginal rate of technical substitution to the ratio of input prices r_1/r_2, it can be seen that farm B enjoys a lower cost of production than farm A of \$ $r_1(x_1^A - x_1^B)$. Given that both farms receive the same price for their output, farm B realizes a higher profit than farm A and is willing to pay more for the right to produce milk. It can then be inferred that facilitating production quota transfers from less efficient to more efficient farms could result in lower average industry costs and ultimately in lower prices for consumers of dairy products.

Under the current regulations, only very small adjustments are possible as there are limits on the quantity of production quota that a farmer can purchase at any point in time. Section VII, paragraph 30 of the *Règlement sur les quotas des producteurs de lait* states that a farmer cannot buy more than 10% of what he could sell, unless the farmer owns less than 12 kg of production quota. This rule severely limits the ability of a farm to get a return on major expansion projects. For example, a farmer with a production quota of 60 kg wanting to triple in size could do so by buying 6 kg of production quota every month for 20 months. Unfortunately, even this timetable is not feasible because the quantity of quota available on the exchange is too low. In 2011, two Quebec dairy farms were heading toward bankruptcy after making large investments to increase their production capacity because they could not buy quota. They got a priority to purchase on the exchange, but questions about the fairness of this decision were raised (La Terre de Chez Nous 2011). Typically, quota can be traded every month on the Quebec exchange, but in 2014 sales were canceled four times because there was not enough quota offered at the price ceiling for buyers to get at least 0.1 kg/butter fat/day each. In October of 2014, 2,180 buyers signaled their intention to buy at the maximum price allowed, but there was only 202.9 kg available and quota could not be traded. Clearly, many dairy producers wish to expand, but under these conditions, it would take over a year to purchase enough quota to add a single cow to a herd. The market generates very little trade and as such it is deficient.

The price ceiling is supported by section VII, paragraph 30 of the *Règlement sur les quotas des producteurs de lait* which states that purchase and selling offers in excess of \$25,000/kg of butterfat/day are unacceptable. Cairns and Meilke (2012) have investigated the rationing effect for Ontario dairy farmers and found that the price-ceiling regulation induces significant welfare losses. In essence, the price-ceiling censors high bids and as such prevents the market from efficiently allocating quota to farmers who could get the highest returns from owning them.[4] To get another perspective on the restrictiveness of the price ceiling on dairy quotas in Quebec, Chernoff (2015) estimated that the price of quotas in 2010 should have been \$7,000 over the \$25,000 ceiling. Expectations about a future increase in the price ceiling or a price-ceiling removal can exacerbate static welfare losses by delaying sales for months or even years. The volume traded has significantly dropped since the imposition of a price ceiling. However, it was difficult to make large purchases even before 2007. One of the reasons is that production quotas cannot be traded across provincial lines. Inefficiencies stemming from this regulation were of a different order in the 1970s when there were many more dairy farms in each province than in 2014. Interprovincial barriers of this sort prevent the exploitation of comparative advantage. Ontario, Nova Scotia, and Quebec allowed interprovincial trading in 1997, but it was quickly terminated in 1998 when Ontario and Nova Scotia pulled out because too much quota was moving to Quebec, an outcome predicted by Lambert et al (1995). Yet, this is the sort of exchanges that need to take place to allow farms to "jump" to more efficient operating scales. Adding production quota by tiny increments is not efficient because some technological investments are lumpy.[5]

[4] Leapfrogging is not possible. The *Règlement sur les quotas des producteurs de lait* prevents a dairy farmer owning a quota to buy, rent, or use another dairy producer's quota with the purpose of using it on his farm, except under special circumstances (e.g., a dairy barn damaged by fire). Generally, a farmer can own only one quota, must own the cows on his farm, and a quota can only be used by one farm. A farm may have up to three dairy barns, but they have to be located within 10 km of one another. Quota transfers are allowed when the purchaser does not already have a quota and intend to use it at the same location. The quota must have been used for at least 5 years at the location prior to the transfer. This prevents the bypassing of the price ceiling as some producers would sell their farm with the entire quota and purchase the farm back with a smaller quota.

[5] For example, adding a milking robot entails adding 60–65 cows (Endres 2008).

The next section discusses how scale and technical efficiency measures can be generated from an input-distance function to shed some light as to why Canada is among the highest cost nations when it comes to the production of milk.

MODEL SPECIFICATION

Dairy farms can be viewed as production units converting inputs like cows, labor, energy, fodder, etc., into primary outputs like milk, other livestock products, and crops. Empirical distance functions have proven to be most convenient to explore scale and technical efficiency measures for multi-output, multi-input technologies (e.g., Morrison-Paul and Nehring 2005). The stochastic input-distance function approach is applied because under Canada's supply management policy and its production quota markets, farmers optimize on their input uses to produce the volume of milk corresponding to their production quota. In other words, producers have more control over their inputs than on the size of their production quota and an input-distance function is better suited than an output-distance function to characterize the technology in such a case (Newman and Matthews 2007). In contrast to the shadow cost model of Mosheim and Lovell (2009), the input-distance function does not require data on input prices. This is an important advantage because reliable input prices at the farm level are not available.

More formally, the input distance $D^I(\mathbf{X}, \mathbf{Y}, t)$ identifies the smallest input vector $\mathbf{X}$ necessary to produce output vector $\mathbf{Y}$, defined according to the set of input vectors $L(\mathbf{Y}, t)$ capable of producing the output vector at time t. It describes how much an input vector may be proportionally contracted holding the output vector fixed. The multi-output input-requirement function allowing for deviations from the frontier is formally defined as follows (Morrison-Paul and Nehring 2005):

$$D^I(\mathbf{X}, \mathbf{Y}, t) = \max\{\rho : \rho > 0, (\mathbf{X}/\rho) \in L(\mathbf{Y}, t)\} \tag{1}$$

where ρ is a scalar, $L(\mathbf{Y}, t)$ is the set of input vectors, $\mathbf{X} = (x_1, \ldots, x_N) \in \mathcal{R}_+^N$ which in year t can produce the output vector $\mathbf{Y} = (\mathrm{y}_1, \ldots, \mathrm{y}_\mathrm{M}) \in \mathcal{R}_+^\mathrm{M}$. The input-distance function can be approximated by the translog functional form, which is flexible in its capacity to approximate arbitrary technologies. It also allows economies of scale to vary for different farm sizes and as such, it limits *a priori* restrictions on the relationships between outputs and inputs (Morrison-Paul et al 2004; Coelli et al 2005, pp. 211–213). The resulting input-oriented translog-distance function is represented as:

$$\begin{aligned}\ln D_t^I(\mathbf{X}, \mathbf{Y}) = \alpha_0 &+ \sum_{n=1}^{N} \alpha_n \ln x_n + \frac{1}{2}\sum_{n=1}^{N}\sum_{k=1}^{N} \alpha_{nk} \ln x_n \ln x_k + \sum_{m=1}^{M} \beta_m \ln y_m \\ &+ \frac{1}{2}\sum_{m=1}^{M}\sum_{l=1}^{M} \beta_{ml} \ln y_m \ln y_l + \sum_{m=1}^{M}\sum_{n=1}^{N} \gamma_{mn} \ln y_m \ln x_n + \sum_{n=1}^{N} \delta_{tx_n} t \ln x_n \\ &+ \sum_{m=1}^{M} \delta_{ty_m} t \ln y_m + \sum_{s=2}^{T} \tau_s C_s + \theta_1 t + \theta_2 t^2\end{aligned} \tag{2}$$

where $D_t^I(\mathbf{X}, \mathbf{Y})$ is a measure of the radial distance from $(\mathbf{X}, \mathbf{Y})$ to the production function, t is a time index ($t = 1, \dots, T$), $C_s (s = 2, \dots, T)$ are time dummy variables taking the value 1 if $S = t$ and zero otherwise, m, l are the outputs, n, k are the inputs, and $\alpha_0, \alpha_n, \alpha_{nk}, \beta_m, \beta_{ml}, \gamma_{mn}, \delta_{tx_n}, \delta_{ty_m}, \tau_s, \theta_1, \theta_2$ are the parameters to be estimated. The regularity conditions associated with the input-distance function are homogeneity of degree one in input quantities (i.e., linear homogeneity inputs) and symmetry. As indicated by Lovell et al (1994), linear homogeneity in inputs implies that the parameters in Equation (2) must be restricted such that: $\sum_{n=1}^{N} \alpha_n = 1$; $\sum_{k=1}^{N} \alpha_{nk} = 0$; $\sum_{n=1}^{N} \gamma_{mn} = 0$ ($m = 1, \dots, M$), and $\sum_{n=1}^{N} \delta_{tx_n} = 0$. The symmetry property is imposed by restricting $\alpha_{nk} = \alpha_{kn}$ ($n, k = 1, \dots, N$) and $\beta_{ml} = \beta_{lm}$ ($m, l = 1, \dots, M$). In the model specification, linear homogeneity is imposed by normalizing the input vector by one of the inputs. The specification of error and efficiency terms follows Battese and Coelli (1992). Rewriting this function by choosing land (x_3) as the normalizing input and including an index i for farms and t for time, results in an equation that can easily be estimated.

$$
\begin{aligned}
-\ln(x_{3it}) = {} & \alpha_0 + \sum_{n \neq 3}^{N} \alpha_n \ln x_{nit}^* + \frac{1}{2} \sum_{n \neq 3}^{N} \sum_{k \neq 3}^{N} \alpha_{nk} \ln x_{nit}^* \ln x_{kit}^* \\
& + \sum_{m=1}^{M} \beta_m \ln y_{mit} + \frac{1}{2} \sum_{m=1}^{M} \sum_{l=1}^{M} \beta_{ml} \ln y_{mit} \ln y_{lit} + \sum_{m=1}^{M} \sum_{n \neq 3}^{N} \gamma_{mn} \ln y_{mit} \ln x_{nit}^* \\
& + \sum_{n \neq 3}^{N} \delta_{tx_n} t \ln x_{nit}^* + \sum_{m=1}^{M} \delta_{ty_m} t \ln y_{mit} + \sum_{s=2}^{T} \tau_s C_s + \theta_1 t + \theta_2 t^2 + v_{it} - u_{it}
\end{aligned} \tag{3}
$$

where $x_{nit}^* = x_{nit}/x_{3it}, \forall n, i, t$, v_{it} represents a random statistical noise, and u_{it} is a one-sided error term representing a technical inefficiency measure with $\ln D_{it}^I(\mathbf{X}_i, \mathbf{Y}_i) = u_{it} \geq 0$, where $D_{it}^I(\mathbf{X}_i, \mathbf{Y}_i) \geq 1$ is the value of the input-distance function of the ith farm using input vector $\mathbf{X}_i$ and producing output vector $\mathbf{Y}_i$ in year t.

Additionally, the theoretical consistency of the estimated stochastic input-distance function requires it to be: (1) nondecreasing in inputs (monotonicity in input) and nonincreasing in outputs (monotonicity in output) and (2) concave in inputs and quasi-concave in outputs. If the estimated parameters violate these assumptions, the computed elasticities and technical efficiency scores can be misleading (Coelli and O'Donnell 2005; Sauer et al 2006). Thus, these necessary conditions are typically tested.

As pointed out by Morrison-Paul and Nehring (2005), coefficient estimates for Equation (3) have the opposite signs from those for a standard input-requirement function. The empirical specification can be estimated as a standard stochastic production frontier with a two-part error term representing deviations from the frontier and random error by maximum likelihood techniques under the assumption that the error term v_{it} is an independently and identically distributed random variable, $N(0, \sigma_v^2)$. The inefficiency terms u_{it} has a time trend component as in Kumbhakar and Lovell (2003, pp. 110–112) and Battese and Coelli (1992):

$$
u_{it} = u_i \exp(-\eta (t - T)) \tag{4}
$$

where u_i are farm specific inefficiency terms assumed to be independently and identically distributed according to a truncated normal distribution $N(\mu_i, \sigma_u^2)$, η is a parameter to be estimated, and T is the last time period.

For the estimation, the error components model is applied as in Battese and Coelli (1992), Morrison-Paul and Nehring (2005), and Rasmussen (2010). To explore the possibility of unobserved heterogeneity between farms, the following three alternatives specifications of the parameter μ_i are tested:

$$\text{Model 1: } \mu_i = 0$$
$$\text{Model 2: } \mu_i = \sum_{k=1}^{K-1} \omega_k A_k$$
$$\text{Model 3: } \mu_i = \sum_{k=1}^{K-1} \omega_k A_k + \sum_{r=1}^{B} \psi_r R_r$$

where A_k refers to age class dummy variables and R_r is production region class dummy variables as in Rasmussen (2010) and Mosheim and Lovell (2009).[6] The level of technical efficiency (TE_{it}) measures how close a given farm i is from the estimated efficient frontier at time t. The deviations of the TE_{it} measures from 1 indicate the percentage by which input use would decrease to reach the production frontier. From Battese and Coelli (1992), the minimum-mean-squared-error predictor of the TE_{it} of the ith farm in period t is

$$TE_{it} = E[\exp(-u_{it}) | v_{it} - u_{it}] \tag{5}$$

From the model specification in Equation (3), various performance indicators are computed. We begin by focusing on the overall **X**–**Y** relationship. The elasticity of the input-distance function with respect to output m is equal to the negative of the elasticity of cost with respect to output m and as such it tells us about the importance of output m in terms of cost. The elasticity of the input-distance function with respect to output m is computed according to

$$\varepsilon_{DY_m} \equiv \frac{\partial \ln D_t^I}{\partial \ln Y_{mt}} = \alpha_m + \sum_{l=1}^{M} \alpha_{ml} \ln Y_{lt} + \sum_{n=1}^{N} \gamma_{mn} \ln x_{nt} + \delta_{ty_m} t \tag{6}$$

The elasticity of the input-distance function with respect to a given input is equal to the cost share of that input:

$$\varepsilon_{DX_n} \equiv \frac{\partial \ln D_t^I}{\partial \ln x_{nt}} = \beta_m + \sum_{k=1}^{N} \beta_{nk} \ln x_{kt} + \sum_{m=1}^{M} \gamma_{mn} \ln Y_{mt} + \delta_{tx_n} t \tag{7}$$

[6] The interpretation of regional effects in the inefficiency term is that as a group, some farmers might face constraints that limit their ability to get the most from their inputs. As pointed out by a reviewer, regional effects could potentially justify the estimation of different frontiers as in Mbaga et al (2003). This would reduce the sample size in the estimation of each frontier. In Mbaga et al (2003), the output elasticities and the average efficiency scores were similar across regions. An alternative would be to introduce a limited number of regional intercept and slope shifters.

The EOS can be computed as

$$\varepsilon_t(\mathbf{X}_t, \mathbf{Y}_t) = -\left[\sum_{m=1}^{M} \frac{\partial \ln D_t^I(\mathbf{X}_t, \mathbf{Y}_t)}{\partial \ln Y_{mt}}\right]^{-1} \tag{8}$$

This measure tells us about the percentage increase in costs in response to a 1% increase in all outputs.

It is well known that total factor productivity (TFP) in the presence of variable returns to scale can be decomposed into a TC component, a technical efficiency change (TEC) component, a scale efficiency change (SEC), and an IME as time passes from period s to period t. An input-oriented measure of TFP change can be written as $TFP = TC \times TEC \times SEC \times IME$. This equation provides a meaningful decomposition of TFP change into four different factors. The term TC captures the shift in technology between two periods evaluated at two different observed output and input vectors. The term TEC measures changes in technical efficiency from one period to the next. The remaining two components, SEC and IME, are defined in terms of the input-oriented scale efficiency measure. The term SEC measures the contribution of scale efficiency to productivity growth. Finally, the term IME measures the impact of changes in the input mix on productivity growth. It measures how the distance of a frontier-point to the frontier of the cone technology changes when input mix changes. Both the scale and input mix terms are the geometric mean of two ratios of input-oriented measures of scale efficiency (Orea 2002). These performance indicators can be computed as follows:

$$TC_{st} = \left[\frac{D_t^I(\mathbf{X}_t, \mathbf{Y}_t)}{D_s^I(\mathbf{X}_t, \mathbf{Y}_t)} \times \frac{D_t^I(\mathbf{X}_s, \mathbf{Y}_s)}{D_s^I(\mathbf{X}_s, \mathbf{Y}_s)}\right]^{0.5} \tag{9}$$

$$TEC_{st} = \frac{D_s^I(\mathbf{X}_s, \mathbf{Y}_s)}{D_t^I(\mathbf{X}_t, \mathbf{Y}_t)} \tag{10}$$

$$SEC_{st} = \left[\frac{ISE_t(\mathbf{X}_t, \mathbf{Y}_t)}{ISE_t(\mathbf{X}_t, \mathbf{Y}_s)} \times \frac{ISE_s(\mathbf{X}_s, \mathbf{Y}_t)}{ISE_s(\mathbf{X}_s, \mathbf{Y}_s)}\right]^{0.5} \tag{11}$$

$$IME_{st} = \left[\frac{ISE_s(\mathbf{X}_t, \mathbf{Y}_t)}{ISE_s(\mathbf{X}_s, \mathbf{Y}_t)} \times \frac{ISE_t(\mathbf{X}_t, \mathbf{Y}_s)}{ISE_t(\mathbf{X}_s, \mathbf{Y}_s)}\right]^{0.5} \tag{12}$$

where ISE_t stands for the input-oriented measure of scale efficiency which is defined as

$$ISE_t(\mathbf{X}_t, \mathbf{Y}_t) = \frac{D_t^I(\mathbf{X}_t, \mathbf{Y}_t)}{D_t^{I*}(\mathbf{X}_t, \mathbf{Y}_t)} \tag{13}$$

and $D_t^{I*}(\mathbf{X}_t, \mathbf{Y}_t) = \max_\lambda D_t^I(\lambda\mathbf{X}_t, \lambda\mathbf{Y}_t)$ is a distance function measured relative to cone technology S_t^* (i.e., an input distance associated with constant returns to scale) which is related to the current technology S_t as follows: $S_t^* = \{(\lambda\mathbf{X}, \lambda\mathbf{Y}), (\mathbf{X}, \mathbf{Y}) \in S_t, \lambda > 0\}$. The S_t exhibits variable returns and as such is less efficient than S_t^* when increasing returns have not been fully exploited or when returns are decreasing. Thus, the distance measured from the technological frontier S_t is weakly inferior to the distance measured from the technological frontier that controls for the efficient scale of production S_t^*. *ISE* tells us how far a farm is to the frontier relative to its distance from a scale-efficient frontier. It takes the form $a/(a + b)$ and a score close to 1 means that the distance between the two frontiers, b, is small relative to the distance between the farm and the regular frontier, a. Doubling both distances, a and b, leaves *ISE* unchanged. Scale efficiency and scale elasticity are two distinct concepts. Evanoff and Israilevish (1995) show that two firms with the same scale elasticity can be at very different distances of their respective scale-efficient level of output. Using the translog specification above and following Pantzios et al (2011), explicit expressions are derived to measure the farm performance. Rasmussen (2010) derived explicit expressions for the input-distance function expressed in terms of the cone technology:

$$\ln D_t^{I*} = \ln D_t^I(\mathbf{X}_t, \mathbf{Y}_t) + \frac{1 - \varepsilon_t(\mathbf{X}_t, \mathbf{Y}_t)}{\alpha\varepsilon_t(\mathbf{X}_t, \mathbf{Y}_t)}\left\{1 - \frac{1}{\varepsilon_t(\mathbf{X}_t, \mathbf{Y}_t)} + \frac{1 - \varepsilon_t(\mathbf{X}_t, \mathbf{Y}_t)}{2\varepsilon_t(\mathbf{X}_t, \mathbf{Y}_t)}\right\} \quad (14)$$

where $\alpha \equiv \sum_{m=1}^{M}\sum_{l=1}^{M}\alpha_{ml}$ and for the input-oriented measure of scale efficiency:

$$\ln ISE_t(\mathbf{X}_t, \mathbf{Y}_t) = -\frac{1 - \varepsilon_t(\mathbf{X}_t, \mathbf{Y}_t)}{\alpha\varepsilon_t(\mathbf{X}_t, \mathbf{Y}_t)}\left\{1 - \frac{1}{\varepsilon_t(\mathbf{X}_t, \mathbf{Y}_t)} + \frac{1 - \varepsilon_t(\mathbf{X}_t, \mathbf{Y}_t)}{2\varepsilon_t(\mathbf{X}_t, \mathbf{Y}_t)}\right\} \quad (15)$$

The IME is perhaps the least intuitive of the TFP components. It refers to the farm's ability to adjust its mix of inputs in response to changes in technology or input quality. Following O'Donnell (2008) and Hadley et al (2013), a simple illustration of the concept is provided in Figure 1. Starting from a technically efficient production level at point B, we assume that an x_1-saving change in technology occurs shifting the isoquant Y^* to Y^{**}. If the input mix remains at B, then there is an input mix inefficiency effect given by CD/OC. Hadley et al (2013) argue that input mix inefficiency is likely in agriculture because of the so-called "putty-clay" nature of technology as some inputs may be difficult to adjust in the short run.

DATA

The data used are farm account series extracted from the database of individual farm accounts collected by the *Groupe Conseils Agricoles du Quebec*. The data set contains farms that are members of management clubs in the province of Quebec. The data set is maintained and updated by the Federation of Management Clubs. The farms included in the database are monitored by management advisers. Data are collected on farm and operator characteristics, revenue and costs of production, marketing practices, production technology, and management practices. We selected dairy farms whose farm cash receipts from their dairy operation made up at least 70% of their farm's total farm cash receipts. As such, these farms are establishments primarily engaged in milking dairy cattle. The full data set comprises 13,398 observations on a total of 2,700 dairy farms that participated in the survey at any time during a 20-year period. The usable sample with complete observations for all variables used in this study consists of 3,994 observations on a total of 1,495 specialized dairy farms covering the 2001–11 period. The number of observations for any given farm varies from 1 to 8. Dairy production is concentrated in the southern part along the St. Lawrence River which accounts for about 70% of the dairy farms in Quebec.

The estimation of distance functions is typically limited to small numbers of outputs and inputs. The data consists of two outputs (milk and beef and other nondairy) and five inputs (feedstuff, labor, land, machinery, and other capital). The aggregation of outputs in the two categories are in line with the characterization made by Mosheim and Lovell (2009) for U.S. dairy farms and Rasmussen (2010) for Danish dairy farms. Cattle is an inevitable by-product of milk production and this is why it is lumped with it. Aggregation of outputs into the above-mentioned product categories is performed by dividing total revenue from all of the outputs by the Törnqvist price index constructed from individual output prices. Following Rasmussen (2010), the general form of the chain version of a Törnqvist price index is calculated as

$$P^{t+1} = \left[\prod_{m=1}^{M} \left\{ \frac{p_m^{t+1}}{p_m^t} \right\}^{1/2\left(s_m^{t+1}+s_m^t\right)} \right] P^t \tag{16}$$

where P^t is the price index of the output aggregate in question (for instance dairy products) in year t, p_m^t is the price of output m in year t, and s_m^t is the revenue share of output m in year t. Other output consists of crop production and includes maize and forages. As maize is the main crop produces by dairy farms, we use maize price as price reference to derive implicit quantity index.

Inputs are aggregated into five categories of aggregate inputs: feedstuff (X_1), labor (X_2), land (X_3), machinery (X_4), and other capital (X_5). Land is expressed in hectares of land cultivated. Labor is the number of workers including the farmer, his family members, and paid labor. The quantity of feedstuff is calculated by dividing the total cost of feedstuff by its Törnqvist price index. The procedure is the same as described above for the aggregation of output. Feedstuff (X_1) includes purchases of concentrates and roughage. Machinery includes the actual cost of machinery which refers to interest, depreciation, maintenance, insurance, contractors, and fuel. Other capital includes interest, depreciation, maintenance, and insurance on buildings, cost of insemination, and control and energy. The output and input prices (p_m^t) used are prices from yearly Agricultural Price Statistics from various sources like *La Financière Agricole du Québec* and *Le Centre d'Expertise en Production Laitière Québec-Atlantique*. Cost shares are determined in a similar way as the revenue shares mentioned above. All input and output variables are mean-corrected prior to estimation, so that the coefficients of the first-order terms can be directly interpreted as distance elasticities evaluated at the geometric mean of the data. From the summary statistics shown in Table 2, we can infer that farm size is highly positively skewed with very few large farms in the sample and that milk-related output sales were on average about four times sales from other outputs.

Table 2. Descriptive statistics of the input and the output variables (units per farm 2001–10)

Variables	Unit	Mean	Min.	Max.
Outputs				
Milk and beef output ($Y1$)	CAN \$	452,210 (333,150)	45,879	3,964,472
Other output ($Y2$)	CAN \$	112,161 (148,525)	1,174	1,462,054
Inputs				
Feedstuff ($X1$)	CAN \$	135,156 (101,785)	21,436	1,250,136
Labor ($X2$)	Num. of workers	2.76 (1.27)	1.1	12.75
Land ($X3$)	Hectares	589.23 (632.21)	84.44	6,108
Machinery ($X4$)	CAN \$	299,589 (236,385)	29,015	2,230,138
Other capital ($X5$)	CAN \$	124,327	243,152	2,429,164

Table 3. Likelihood ratio tests on specification of inefficiency term

Models	Log likelihood	Wald χ^2 statistics	Log likelihood ratio
Model 1: $\mu_i = 0$	537.99	8,272 (40)	
Model 2: $\mu_i = \sum_{k=1}^{K-1} \omega_k A_k$	540.29	8,299 (41)	4.61*
Model 3: $\mu_i = \sum_{k=1}^{K-1} \omega_k A_k + \sum_{r=1}^{B} \psi_r R_r$	543.90	8,430 (43)	7.22**

Note: **Significant at 5% level.
*Significant at 10% level.

RESULTS AND DISCUSSIONS

Specification Testing

To arrive at the final specification, different alternative specifications are considered as mentioned in section "Model Specification." We begin by testing for age and regional effects. As in Rasmussen (2010), farmers are classified as young ($k = 1$) if they are below the age of 45 years, as old ($k = 3$) if they are 60 years or older, and as middle aged ($k = 2$) if they are in between. Constraints limiting agricultural productions may vary across administrative regions and this is why the 17 administrative regions of Quebec are grouped into three regions: the southern region ($R = 1$) which includes Estrie, Montérégie, and Centre-du-Québec; the northern region ($R = 3$) which is made up of Bas-Saint-Laurent, Saguenay-Lac-Saint-Jean, Capitale-Nationale, Outaouais, Abitibi-Temiscamingue, Côte-Nord, Nord-du-Québec, Gaspésie-îles-de-la-Madeleine, and Chaudière-Appalaches; and the central region ($R = 2$) which comprises Mauricie, Montreal, Laval, Lanaudière, and Laurentides.

The likelihood ratio test for the specification of the inefficiency term is presented in Table 3. To ascertain whether age impacts on distance-based performance measures, a test comparing the log-likelihood from Model 1 (restricted) to the log-likelihood of Model 2 (unrestricted) is conducted. The test rejected the null that both models are equivalent and it is concluded that age matters. Similarly, regional differences are found to be statistically significant, which is not surprising considering that climate differences allow some crops to grow better in some regions but not in others.

The second set of tests pertained to the theoretical consistency of the estimated stochastic input-distance function. As indicated by many authors such as Sauer et al (2006), the estimated parameters must support the assumptions of monotonicity and quasi-concavity for elasticities and technical efficiency estimates to be valid. The function must be decreasing in outputs for the scale effect to be correctly measured. The maximum likelihood parameter estimates of the translog input-distance function (Equation [3]) are reported in Table 4.The first-order coefficients can be interpreted as distance elasticities evaluated at the sample mean, since each output and input variable has been divided by its geometric mean. Moreover, the property of linear homogeneity in inputs is imposed using land as the numeraire. Similarly, the time trend parameter (θ_1) captures the linear effect of time on the growth of the distance while θ_2 allows for time to have a quadratic effect. The sum $\theta_1 + \theta_2 t$ measures the annual rate of disembodied TC by the average farm and δ_{tx_n} and δ_{ty_m}, respectively, estimate the annual rate of change in the sample average farm's estimated input elasticities and output elasticities.

All first-order coefficients have the expected signs ($\alpha_n > 0$ for all n inputs and $\beta_m < 0$ for all m outputs), implying that the input-oriented distance function is nonincreasing in output quantities and nondecreasing in input quantities at the sample mean. These results indicate that monotonicity conditions were fulfilled at the sample mean. Monotonicity was also tested for the entire sample. As revealed in Table 5, except for other capital, all partial derivatives of the distance function are of the appropriate sign at the sample mean with few violations of the monotonicity assumption throughout the sample as a whole.[7] Additionally, at the point of approximation, the Hessian matrix was negative-definite with respect to outputs and positive-definite with respect to inputs. This indicates that the estimated input-distance function is concave in inputs and quasi-concave in outputs. The estimated input-distance function therefore seems quite robust in fulfilling the theoretical conditions of being nondecreasing and concave in inputs and nonincreasing and quasi-concave in outputs. The variance parameters, σ^2 and γ in Table 4, are statistically significant at the 5% level. Moreover, the ratio parameter γ is estimated at 0.84 indicating that technical inefficiency plays a significant role in explaining output variability among the dairy farms in the sample.

Estimated Technical Efficiency, Input Scale Efficiency, and the Elasticity of Scale

The mean technical efficiency is calculated for each year using the weighted average of u_{it} as in Equation (5). The results are shown in Table 6 as along with estimates of the EOS and the input scale efficiency (ISE) which are computed using weighted averages of explanatory variables within each year.

[7] Local regularity restrictions are often imposed on translog cost or revenue functions. This way, the functional form remains flexible, but there is no guarantee that all violations will be purged except for the year at which the restrictions are imposed (e.g., Chapda Nana and Larue 2014). Regularity conditions are less often imposed by users of input-distance functions. O'Donnell and Coelli (2005) propose a Bayesian framework to impose monotonicity, quasi-convexity, and convexity constraints on output-distance functions.

Table 4. Estimated parameters (Model 3)

Variable	Coefficient	Standard error	t-Ratio
Constant (α_0)	−0.0540*	0.0328	−1.65
Ln feed (α_1)	0.6602***	0.0487	13.53
Ln labor (α_2)	0.2668***	0.0437	6.09
Ln mach. (α_3)	0.1004***	0.0282	3.56
Ln otherCap. (α_4)	0.0048	0.0054	0.89
Ln feed × Ln feed (α_{11})	0.0723	0.0557	1.30
Ln labor × Ln labor (α_{22})	−0.0245	0.0397	−0.62
Ln mach. × Ln mach. (α_{33})	0.0098	0.0212	0.46
Ln otherCap. × Ln otherCap. (α_{44})	−0.0005	0.0011	−0.49
Ln feed × Ln labor (α_{12})	−0.0959	0.0831	−1.15
Ln feed × Ln mach. (α_{13})	0.0153	0.0550	0.28
Ln feed × Ln otherCap. (α_{14})	0.0053	0.0104	0.51
Ln labor × Ln mach. (α_{23})	0.0482	0.0512	0.94
Ln labor × Ln otherCap. (α_{24})	0.0016	0.0095	0.17
Ln mach. × Ln otherCap. (α_{34})	−0.0077	0.0066	−1.15
Ln milk (β_1)	−0.8149***	0.0351	−23.18
Ln otherOutp. (β_2)	−0.0710***	0.0171	−4.14
Ln milk × Ln milk (β_{11})	−0.1588***	0.0207	−7.64
Ln otherOutp. × Ln otherOutp. (β_{22})	−0.0081	0.0060	−1.34
Ln milk × Ln otherOutp. (β_{12})	0.0800***	0.0204	3.92
Ln feed × Ln milk (γ_{11})	0.1602**	0.0572	2.80
Ln feed × Ln otherOutp. (γ_{12})	−0.0844**	0.0282	−2.99
Ln labor × Ln milk (γ_{21})	−0.1352	0.0498	−2.71
Ln labor × Ln otherOutp. (γ_{22})	0.0724**	0.0252	2.87
Ln mach. × Ln milk (γ_{31})	0.0075	0.0394	0.19
Ln mach. × Ln otherOutp. (γ_{32})	−0.0108	0.0191	−0.57
Ln otherCap. × Ln milk (γ_{41})	0.0072	0.0066	1.09
Ln otherCap. × Ln milk (γ_{42})	0.0004	0.0035	0.14
Time × Ln feed (δ_{tx_1})	−0.0095	0.0067	−1.42
Time × Ln labor (δ_{tx_2})	0.0057	0.0060	0.94
Time × Ln mach. (δ_{tx_3})	0.0001	0.0038	0.002
Time × Ln otherCap. (δ_{tx_4})	−0.0011	0.0008	−1.44
Time × Ln milk (δ_{ty_1})	0.0091*	0.0046	1.97
Time × Ln otherOutp. (δ_{ty_2})	0.0020	0.0023	0.86
Time (θ_1)	−0.0583***	0.0163	−3.57
Time square (θ_2)	0.0045**	0.0015	3.02
Time dummy for 2002 (τ_{2002})	0.0152	0.0158	0.96
Time dummy for 2005 (τ_{2005})	0.1918***	0.0296	6.48
Time dummy for 2006 (τ_{2006})	0.1743***	0.0297	5.87
Time dummy for 2007 (τ_{2007})	0.1645***	0.0265	6.20
Time dummy for 2008 (τ_{2008})	0.0892***	0.0204	4.36
Young head: Age <45 years (ω_1)	−0.0023	0.0165	−0.14
Old head: Age >60 years (ω_2)	−0.0281*	0.0154	−1.82
Dummy for southern region (ψ_1)	0.0380*	0.0154	2.46

(*Continued*)

Table 4. Continued

Variable	Coefficient	Standard error	t-Ratio
Dummy for northern region (ψ_2)	0.0016	0.0151	0.11
$\sigma^2 = \sigma_v^2 + \sigma_u^2$	0.0296***	0.005	
γ	0.8412***	0.0326	
η	−0.0205	0.0139	−1.47
Log likelihood	543.90		

Note: ***Significant at 1% level.
**Significant at 5% level.
*Significant at 10% level.

Table 5. Elasticities of input-distance function at the sample means

Variables	Elasticities	Std.	Violations (%)
Milk and beef output ($Y1$)	−0.7596	0.1220	0
Other output ($Y2$)	−0.0589	0.0312	2.73
Feedstuff ($X1$)	0.6025	0.1160	0
Labor ($X2$)	0.3014	0.0893	0
Machinery ($X4$)	0.1008	0.0329	0.36
Other capital ($X5$)	−0.0023	0.0054	64.30

Note: For output, violations consist of percentage of positive elasticities while for inputs, violations consist of percentage of negative elasticities.

Table 6. Predicted technical efficiency (TE), elasticity of scale (EOS), and input scale efficiency (ISE) based on weighted average over farms within each year

Year	TE	EOS	ISE
2001	0.881 (0.065)	1.249 (0.142)	0.920 (0.062)
2002	0.877 (0.069)	1.264 (0.144)	0.914 (0.063)
2005	0.866 (0.072)	1.241 (0.140)	0.923 (0.060)
2006	0.878 (0.069)	1.229 (0.136)	0.928 (0.059)
2007	0.873 (0.073)	1.224 (0.306)	0.932 (0.094)
2008	0.872 (0.072)	1.211 (0.142)	0.933 (0.058)
2009	0.881 (0.071)	1.259 (0.157)	0.912 (0.064)
2010	0.877 (0.071)	1.233 (0.155)	0.923 (0.063)
Average	0.876 (0.070)	1.240 (0.170)	0.922 (0.066)

Note: Standard deviations in parentheses.

Technical efficiency

The estimated mean technical efficiency is 88% during the period under consideration, ranging from a minimum of 68% to a maximum of 99%, while the average standard deviation is 7%. Figure 2 presents the distribution of technical efficiency scores. The distribution is clearly negatively skewed with the bottom 25% of farms with scores varying

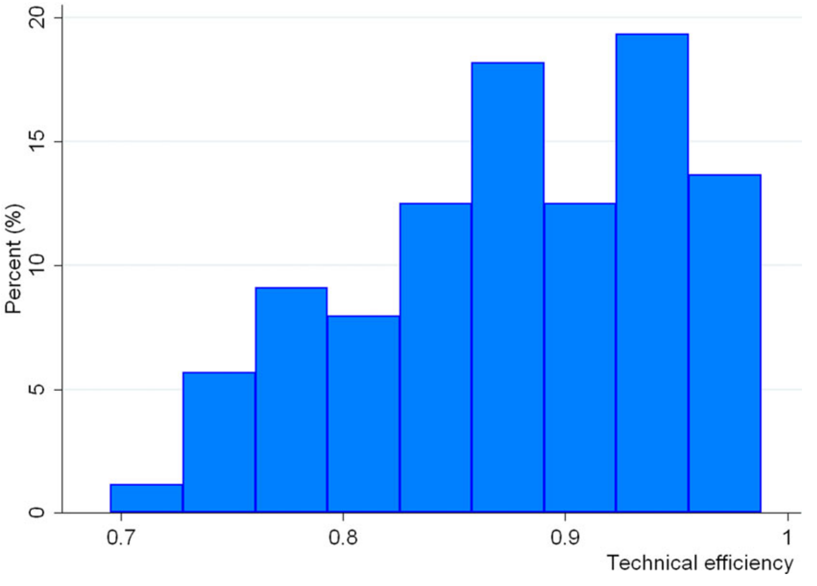


Figure 2. Distribution of Quebec dairy farms' technical efficiency scores

between 68% and 83%. These estimates are comparable with those reported in previous studies about Quebec's dairy sector.[8] Mbaga et al (2003), using cross-sectional data, found an average-level technical efficiency of 94%. Correcting for heterogeneity with threshold effects in panel data stochastic frontier models, Yélou et al (2010) found an average technical efficiency level of 97%. Cloutier and Rowley (1993) relied on a nonparametric data envelopment approach and found technical efficiency averages of 88% and 91% for 1988 and 1989. Using a deterministic nonparametric frontier technology approach, Weersink et al (1990) reported a mean efficiency estimate of 92% for Ontario dairy farms. Hailu et al (2005) found similar results for Ontario over the 1984–96 period. As found by Rasmussen for Danish dairy farms, Table 6 shows that average technical efficiency levels have not changed much over time. The variations are not statistically significant since the estimated value of parameter η (see Equation [4] and Table 4), though negative, is not significant. This is not surprising because there have not been major technological breakthroughs or animal diseases that could have induced large differences in farm performance during the period covered.

To examine the robustness of the obtained technical efficiency measures to rigidities on the production quota market, the model over the shorter 2007–10 period is also estimated. During this period, the price-ceiling regulation on quota values was binding.

[8] A technical efficiency score is a relative indicator that pits a farm against a frontier defined by the most efficient farms in the sample. Similarly, parameters and values used to compute elasticities of scale are sample dependent. Given that Quebec farms are quite homogenous and operate in a stable environment, high average efficiency scores are to be expected. The implication is that a high average level of technical efficiency can emerge from a sample of high-cost or low-cost firms as long as firms in the sample perform similarly.

The Spearman's rank correlation of 0.932 indicates that the rankings of farms in terms of technical efficiency produced from the 2001–10 and 2007–10 samples are very similar. While the price-ceiling regulation in Quebec has assuredly created the same kind of decline in buyer and seller surplus and welfare losses documented by Cairns and Meilke (2012) for Ontario, the good news was that technical efficiency has not been impacted. This is due in part to a low farm turnover. The rate of decline in the number of farms in Quebec and Ontario is 4.77% between 2000 and 2007 and about the same, 4.56% for British Columbia, Alberta, and Manitoba. For the 2008–14 period, the respective rates of decline fell to 1.74% and 2.96%.

The estimated parameters ω_k of the inefficiency term in Table 4 reveal that technical efficiency decreases with age (the middle age is used as reference). Older farmers have a significantly lower level technical efficiency than middle aged farmers, as for the Danish dairy sector in Rasmussen (2010). The estimated parameters ψ_r show that dairy farms in the southern region of Quebec are more technically efficient than farms located in the center of the province. There is no difference between farms located in the north and in the center of the province. Accordingly, extension activities should target older producers that may not be exploit technological innovations as easily as younger producers as well as producers located in regions with colder climate and less productive land.

Elasticity of scale and input scale efficiency

Table 6 shows that the average EOS is statistically significant and greater than 1, confirming the presence of increasing returns to scale. On average, only 2.73% of the dairy farms have an EOS less than 1.00. Similar results were reported in Hailu et al (2005) for Alberta and Ontario dairy farms over the period of 1984–96, by Moschini (1988) for Ontario dairy farms as well as by Richards and Jeffrey (2000) for Alberta dairy farms. Morrison-Paul et al (2004) also argued that scale economies are greatest for smaller U.S. farms. The implication is that lower average costs can be achieved by producing at a larger scale. Interestingly, results in Mosheim and Lovell (2009) suggest that such cost-reducing effects remain present for herd sizes much larger than the largest ones in our sample. The results in Table 6 also indicate that the EOS for Quebec dairy farms has not changed very much over time even though the average Quebec dairy farm has grown over time. This suggests that farm size has not increased fast enough over time. This result is important for policy purposes because additional concessions on market access, through bilateral trade agreements like the Canada-EU Comprehensive Economic and Trade Agreement and the Trans-Pacific Partnership (TPP), or multilaterally through the World Trade Organization (WTO), could make production even less efficient if growth in the national quota is going to be reduced.

The ISE results in Table 6 indicate that scale efficiency is greater than technical efficiency. Average input-oriented scale efficiency over farms and time is found to be 92.27%, 4.6% higher than the average technical efficiency (the average standard deviation is 6.62%). In particular, ISE scores ranges from a minimum of 39.30% to a maximum of 99.99%. However, the vast majority of dairy farms (more than 87%) in the sample have achieved ISE scores between 85% and 100%. This result implies that many dairy farms in Quebec operate at suboptimal scale, but are fairly close to constant returns to scale. The mean scale efficiency fluctuated over time around its period average, but the 2001 and 2010 ISE averages are essentially identical. This confirms that scale efficiency of dairy

Table 7. Estimates of technical efficiency (TE), elasticity of scale (EOS), and input scale efficiency (ISE) by farm size

Herd size	TE	EOS	ISE
Herd < 10	0.886 (0.052)	1.409 (0.286)	0.855 (0.091)
$10 \leq$ Herd < 20	0.867 (0.069)	1.316 (0.131)	0.891 (0.063)
$20 \leq$ Herd < 30	0.873 (0.068)	1.195 (0.093)	0.944 (0.039)
$30 \leq$ Herd < 40	0.888 (0.074)	1.154 (0.099)	0.959 (0.038)
$40 \leq$ Herd < 50	0.883 (0.079)	1.112 (0.110)	0.969 (0.033)
$50 \leq$ Herd < 60	0.932 (0.074)	1.091 (0.086)	0.979 (0.024)
Herd ≥ 60	0.842 (0.088)	0.984 (0.090)	0.979 (0.038)

Note: Standard deviations in parentheses.

farms in Quebec has not improved over time. Progress was made between 2001 and 2008, but it was quickly dissipated between 2008 and 2010 possibly due the drop in the volume of quota traded after the price ceiling on production quota was imposed.

The second-order effects in Table 4's coefficients can be used to further characterize the marginal cost of milk production. As stated previously, the input elasticity for milk output Y_m is $-\varepsilon_{D^I, Y_m} = -\partial \ln D^I/\partial \ln Y_m = \partial \ln X_3/\partial \ln Y_m = \varepsilon_{X, Y_m}$. This elasticity is conditioned by the inputs and outputs in the distance function and it represents the percentage input expansion required for a 1% increase in Y_m, holding all input ratios and the other output constant. Following Morrison-Paul and Nehring (2005), the duality between input-distance and cost functions allow us to interpret $\partial X_3/\partial Y_m$ as the marginal cost of Y_m (an increase in all inputs from an increase in Y_m, MC_m). Of particular interest is how changes in the milk output are affecting the elasticity of milk output $\varepsilon_{X, Y_m, Y_m} = \partial \varepsilon_{X, Y_m}/\partial \ln Y_m$. This derivative tells us how the ratio of marginal and average costs has changed from an increase in milk output. From the translog specification, the derivative $\beta_{11} = \varepsilon_{X, Y_m Y_m}$ is negative and significant at the 1% level, implying that input use increases in response to increases in milk production get smaller at higher levels of milk production. This means that the ratio of marginal and average costs of milk becomes smaller as milk output increases. When variations in all outputs are accounted for, the elasticities of scale by herd size reported in Table 7 show that the largest farms in the sample face constant returns to scale. Mosheim and Lovell's (2009) scale elasticities increased when herd size increases from less than 30 cows to 30–50 cows, stay constant for herd sizes between 50 and 200 cows, decreased for herd size between 200 and 1,000 cows, and stay constant as herd size increases beyond 1,000 cows. Not surprisingly, their scale elasticities for smaller farms, which vary between 1.8 and 2.5, are higher than the mean elasticity of 1.24 for Quebec dairy farms (see Table 6).

Source of Productivity Change

The parametric decomposition of TFP is implemented in this section. The components of productivity growth are calculated by applying the approach of Pantzios et al (2011) and Rasmussen (2010). Estimates of the input-distance Malmquist productivity index and its components are reported in Table 8. According to these estimates, productivity increased at an average annual rate of 8.8% between 2001 and 2010. This can be interpreted as

Table 8. Indices of year-to-year changes in technical efficiency change (TEC), technical change (TC), scale (SEC), input-mix effect (IME), and total factor productivity (TFP)

Year	TEC	TC	SEC	IME	TFP
2005					
2006	0.997	0.993	1.007	1.072	1.069
2007	0.996	1.002	1.018	1.086	1.105
2008	0.996	1.012	1.008	1.075	1.093
2009	0.996	1.019	1.008	1.082	1.108
2010	0.997	1.029	1.003	1.078	1.111
Average	0.997	1.001	1.008	1.080	1.088

an annual improvement in the input–output relation, which increased output (reduces input) for a given input (output) at a rate of 8.8% per year on average. The highest growth rates of productivity are observed at the end of the decade. As for the sources of this growth, it can be seen from Table 8 that TC, SEC, and the IME have contributed positively to productivity growth, whereas the temporal change in technical efficiency has had an adverse effect on productivity growth. The most important component of productivity growth is IME, as in Hadley et al's (2013) study about hog production in the United Kingdom. The average value of the IME indicate that scale efficiency associated with the input combinations used in two successive periods—conditional on the same output mix—increases at an annual rate of 8.05%. In addition, the average value of the SEC component indicates that the radial scale efficiency associated with the output combinations produced in two successive periods—conditional on the same input mix increases at an annual rate of 0.85%. Since farms have not been able to expand very much, this result is hardly surprising. The temporal changes of TC also increased at an annual rate of 0.14%. This implies that the production frontier (isoquants) shifted outward (inward), but at a slow pace. As indicated by Sipiläinen (2007) for Finnish dairy farms, the relief of quota restrictions could increase the enlargements of farms as well as the adoption of improved production technologies. A similar conclusion was reached by Kumbhakar et al (2008) who found that a tight milk quota policy had an adverse effect on TC on Norway dairy farms. On the other hand, technical efficiency associated with the production technology used in two successive periods—conditional on the same output–input mix—decreased at an annual rate of 0.29%. However, the IME associated with the scale effect was strong enough to outweigh the negative effect of TECs on productivity. Hence, the "scale effect," that is, the combined contribution of radial SECs and SECs associated with temporal changes in the input mix raises productivity by 8.8%. As in Pantzios et al (2011), an overall positive impact of the "scale effect" had to be expected given the presence of increasing returns.

CONCLUDING REMARKS AND POLICY IMPLICATIONS

Canada's costs of production for milk are the third highest in the world according to IFCN (2012). Quebec is the largest producing province and past studies have shown that its small dairy farms operated at high levels of technical efficiency. Regulations in the dairy industry have implicitly assumed that economies of scale were nonexistent. This has been reinforced by statements made by farm management experts, as the quote at the beginning of this paper made abundantly clear. The purpose of the present study is to ascertain the validity of the nonincreasing returns assumption and to compare the importance of different performance indicators in milk production in Quebec. To this end, the paper focuses on economies of scale estimates and the evolution of TFP and its components by estimating a stochastic input-distance function on a sample of Quebec dairy farms.

It is found that Quebec dairy farms could reduce their average cost by operating at a higher scale of production and by improving technical efficiency, the mean efficiency score being 0.87 for the 2001–10 period. The results also show that scale efficiency is greater than technical efficiency. These results are not surprising given that the distribution of Quebec dairy is highly skewed toward small homogenous farms and that technical and scale efficiency scores are based on efficiency benchmarks defined by farms in the sample. TFP has grown at an average rate of 9%, thanks largely to IMEs. The contributions of TC and ISE to TFP growth are very small. These results suggest that most Quebec dairy farmers are good managers operating at a suboptimal scale, facing increasing returns to scale. Clearly, the exploitation of economies of scale could bring about reductions in average costs. The rate of TC for small farms in the sample has been quite low. This was also observed in countries that have milk quotas (e.g., Sipiläinen 2007; Kumbhakar et al 2008). Some technological advances in milk production are tailored to large farms and small farms are likely to be increasingly disadvantaged.[9]

Our results have important implications for domestic policy and especially for the markets for production quotas. The large numbers of Quebec dairy farmers wishing to buy quota and the small quantities offered every month at the maximum price are indicative of a dysfunctional quota market. Regulations pertaining to the quantity that an individual producer can buy, the maximum acceptable bid on the Quebec exchange, as well as the inability of Quebec dairy producers to buy quotas on other provincial exchanges, have created extreme rationing outcomes. The ratio of quantity demanded and quantity offered has been so high that monthly exchanges had to be canceled four times in 2014, as the minimum of 0.1 kg/day per buyer at the price ceiling could not be met. Even when transactions are taking place, the volume is so low that it would take months of purchases for a producer to get enough quotas to add a single cow to his/her herd.[10] For the industry to better cope with foreign competition, it will be important to create conditions allowing dairy producers with lower cost of production to buy production quotas from dairy producers with higher costs of production. The resulting lower milk prices at the farm level would create gains downstream, for processors, retailers, and consumers. Dairy farmers wishing to exit the sector would get a fair compensation from dairy farmers with low enough production costs to face greater competition. The resulting lower prices may

[9] For example, large farms that use a rotary milking system can milk 250 cows per hour while small farms relying on a parallel parlor can milk 75 cows per hour (http://en.wikipedia.org/wiki/Dairy_farming). As pointed out by a reviewer, some technological advances, like embryo transfer, benefit small and large farms.

[10] For example, 544 kg/day was offered by 54 producers and 11,834 kg/day was demanded by 2,165 producers on the Quebec exchange in November of 2014.

create yet a new source of benefits: induced productivity gains. Chernoff (2014) analyzed participation by Quebec dairy farms in the commercial export milk program that allowed production without quota between 2000 and 2003. He found evidence of self-selection in the participation and a strong causal effect from export exposure to productivity.

Our results also have implications for trade policy. Accommodations will be made to allow for more cheese imports from the European Union (EU) because of the Canada–EU trade agreement and more market access concessions might follow once the TPP negotiations are concluded. Having granted preferential access to the EU, Canada will be able to count on a powerful ally to protect supply management at the WTO, but giving up access to the EU and perhaps other foreign countries will bring about a reduction in the portion of the domestic market left to domestic dairy producers, hence exacerbating the scale problem of Canadian dairy farms (Larue et al 2007). The lowering of overquota tariffs would not have the same reducing effect on national production as the enlargement of the Tariff-Rate Quotas and hence must be considered in regional and multilateral negotiations.

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