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Economies of Scale in the Canadian Food Processing Industry

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Abstract: Cost functions for three Canadian manufacturing agri-food sectors (meat, bakery and dairy) are estimated using provincial data from 1990 to 1999. A translog functional form is used and the concavity property is imposed locally. The Morishima substitution elasticities and returns to scale elasticities are computed for different provinces. Inference is carried out using asymptotic theory as well as bootstrap methods. In particular, the ability of the double bootstrap to provide refinements in inference is investigated. The evidence suggests that there are significant substitution possibilities between the agricultural input and other production factors in the meat and bakery sectors. Scale elasticity parameters indicate that increasing returns to scale are present in small bakery industries. While point estimates suggest that increasing returns to scale exist at the industry level in the meat sector, statistical inference cannot rule the existence of decreasing returns to scale. To account for supply management in the dairy sector, separability between raw milk and the other inputs was introduced. There exists evidence of increasing returns to scale at the industry level in the dairy industries of Alberta and New Brunswick. The scale elasticity for the two largest provinces (Ontario and Quebec) is greater than one, but inference does not reject the null hypothesis of increasing returns to scale.

Keywords: Translog cost function, Canadian food processing industry, returns to scale, double bootstrap

J.E.L. Classification: D24, C30

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Economies of Scale in the Canadian Food Processing Industry

1 – Introduction

Broad globalization forces are changing the competitive environment of Canadian agri-business firms. One factor that is often identified by firms to potentially increase their competitiveness is achieving economies of scale by expanding production. If increases in output lower average costs of processing firms, these benefits can increased profits or be passed back to consumers and/or upstream agricultural producers; thus improving efficiency in the entire supply chain. Canada is a medium-sized economy highly dependent on trade. The United States is the most important export market of Canadian firms; but U.S. firms also often represent the strongest competition of Canadian processors selling abroad (Baldwin, Sabourin and West, 1999). A significant literature already documents economies of scale in the U.S. meat processing industry (*e.g.,* Ball and Chambers, 1982; Macdonald and Ollinger, 2000; Morrison Paul, 2001a and 2001b; Ollinger, MacDonald and Madison, 2005). Data availability issues or the belief that technology and input prices are similar across industries in the two countries can perhaps explain why relatively little empirical work has been done to date on measuring economies of scale in the Canadian food processing sector. While similarities between the two countries' industries undoubtedly exist, there are fundamental differences that make extending the conclusions drawn in the U.S. case to the Canadian case questionable. Identifying these differences is crucial in the current globalization environment.

This study uses Statistics Canada's Annual Survey of Manufactures (ASM) to estimate economies of scale at the industry level in the meat, dairy and bread and bakery sectors of each province. A translog cost function with four inputs (material, capital, labour and energy) is estimated. The homogeneity, symmetry and adding-up properties of the cost function are imposed through cross-equations restrictions while concavity is imposed locally using the methodology of Ryan and Wales (2000). The model is estimated using maximum likelihood techniques. Inference in the model is carried out using McCullough and Vinod (1998)'s double bootstrap procedure because it produces more precise confidence intervals for the elasticities. The refinements induced by the double bootstrap procedure are illustrated using comparisons with the usual asymptotic inference procedure and single bootstrap method.

Two important issues emerged at the modelling stage. First, it is essential that the empirical model considers the effects of supply management on the decisions of Canadian dairy processors. Supply management is introduced through a restriction on the technology by assuming that material (raw milk) is a perfect complement to the basket of other inputs. The assumption of fixed proportion between output, raw milk and the basket of other inputs satisfies the condition that the total quantity of milk available to processors is predetermined in the cost minimization process. More importantly, it also implies that changes in output of processed dairy products are accompanied by proportional changes in the supply of raw milk.

The second issue refers to the available dataset and the interpretation of the scale elasticities. Economies of scale at the industry level can come from three different sources. Unit cost at the plant or firm level can fall as the scale of production increases given factor prices. Plant level economies of scale are often linked to heavy manufacturing industries while firm level returns to scale are associated with advertising, product design, research, etc. (Arrow, 1998). Moreover, even if all firms produce under constant returns to scale, it is still possible to find increasing returns to scale at the industry level independently of the number of firms in the industry. In this case, increasing returns are external to the firm. There can be a number of different sources for external economies of scale: specialized suppliers, labour market pooling and human capital accumulation, knowledge spillovers, etc. Hence, it is important to understand that finding economies of scale at the industry level does not constitute evidence that firms can lower their average costs by increasing output. Data availability issues prevent making useful comparisons between the Canadian and U.S. industries because it is not possible in the present case to identify plant and/or firm level returns to scale. Nevertheless, discovering increasing returns to scale at the industry level would suggest that output growth and/or reallocation across firms can lead to cost savings and thus improve competitiveness.

The remainder of the paper is structured as follows. The next section presents the empirical model and discusses the properties of the cost function. Section 3 introduces the data and provides a brief description of general trends in the three industries. Section 4 presents the estimation results, introduces the inference methods and discusses the policy implications of the findings. The last section summarizes the results and suggests future research avenues to explore.

2 – Empirical model

Let C represent total expenditures on material (M), labour (L), capital (K) and energy (E) by all firms in a given sector. Define Q as the industry output and let $p_j\left(j = M, L, K, E\right)$ be the price of the j^{th} input. The cost function is approximated by a translog flexible functional form (Christensen, Jorgenson and Lau, 1973):

$$\begin{aligned}\ln C = {} & \alpha_0 + \alpha_Q \ln Q + 0.5\alpha_{QQ}\left(\ln Q\right)^2 + \sum\nolimits_{i=1}^{4} \alpha_i \ln p_i + \sum\nolimits_{i=1}^{4} \alpha_{iQ} \ln p_i \ln Q \\ & + 0.5\sum\nolimits_{j=1}^{4}\sum\nolimits_{i=1}^{4} \alpha_{ij} \ln p_i \ln p_j + \alpha_t t + 0.5\alpha_{tt} t^2 + \sum\nolimits_{i=1}^{4} \alpha_{it} t \ln p_i + \alpha_{tQ} t \ln Q\end{aligned} \tag{1}$$

where t is a time trend. Cost minimization and Shephard's lemma imply:

$$w_i = \alpha_i + \alpha_{iQ} \ln Q + \sum\nolimits_{j=1}^{4} \alpha_{ij} \ln p_j + \alpha_{it} t; \quad i = 1, \ldots, 4 \tag{2}$$

where w_i is the i^{th} input expenditure share. Homogeneity, adding-up and symmetry properties imply that:

$$\sum_i^4 \alpha_i = 1,\ \sum_i^4 \alpha_{iQ} = 0,\ \sum_{i=1}^4 \alpha_{ij} = 0\ \forall j,\ \sum_{i=1}^4 \alpha_{it} = 0, \text{ and } \alpha_{ij} = \alpha_{ji} \tag{3}$$

Unfortunately, no parametric restrictions can simultaneously preserve the flexibility of the translog cost function while guaranteeing that concavity in prices will be respected. The concavity property of the translog cost function is data dependent. Ryan and Wales (2000) showed how to impose concavity at a single point while preserving the global flexibility of the cost function.[1] While there is no assurance that their approach improves the overall number of observations for which concavity is respected, they report that their method works extremely well for their empirical application (*i.e.* concavity is automatically verified at all points).

Let **H** be the Hessian of the cost function defined in (1). Moreover, let p^*, Q^* and t^* represent the normalization points. In the empirical application that follows, they will represent the province of interest for a specific year. It can be shown that the elements of the Hessian evaluated at the normalization points are only function of the parameters of the model (Diewert and Wales, 1987):

$$H_{ij} = \alpha_{ij} - \delta_{ij}\alpha_i + \alpha_i\alpha_j;\ i, j = 1,\ldots,4 \tag{4}$$

where $\delta_{ij} = 1$ if $i = j$ and 0 otherwise. The Hessian can be expressed as the product of a lower triangular matrix **D** (with elements d_{ij}) by itself; *i.e.*, $\mathbf{H} = -\mathbf{DD}'$ which by definition is negative semi-definite. Hence, (4) can be rewritten as:

$$\alpha_{ij} = -\left(\mathbf{DD}'\right)_{ij} + \delta_{ij}\alpha_i - \alpha_i\alpha_j \tag{5}$$

The parametric restrictions in (5) are imposed when estimating the cost function in (1) and expenditures shares in (2). It is relatively straightforward to show that:

$$\alpha_{11}=-d_{11}^2+\alpha_1-\alpha_1^2;\quad \alpha_{22}=-d_{21}^2-d_{22}^2+\alpha_2-\alpha_2^2;\quad \alpha_{33}=-d_{31}^2-d_{32}^2-d_{33}^2+\alpha_3-\alpha_3^2$$
$$\alpha_{12}=-d_{11}d_{21}-\alpha_1\alpha_2;\quad \alpha_{13}=-d_{11}d_{31}-\alpha_1\alpha_3;\quad \alpha_{23}=-d_{21}d_{31}-d_{22}d_{32}-\alpha_2\alpha_3 \tag{6}$$

The parameters of the 4th input share equation are retrieved using the adding-up property. Equations (1) and (2) are estimated by maximum likelihood once restrictions in (3) and (6) have been included in the cost function and expenditure shares. The restricted system has the same number of parameters as in (1) and thus Ryan and Wales' methodology preserves the flexibility of the translog cost function.

Canadian dairy production is under supply management and thus administered decisions in the dairy industry will likely have impacts on the cost structure of processing firms. Assuming that expenditures in material mainly include raw milk, material is not a choice variable from the industry perspective and is a predetermined variable in the cost minimization process. It is assumed that production of dairy products in a given province is determined according to the Leontief-type technology: $Q=G\left(M,K,L,E\right)=\min\left\{\alpha_{0M}M^{\alpha_{1M}},F\left(K,L,E\right)\right\}$. The production process $G\left(\bullet\right)$ implies that there are no substitution possibilities between material (milk) and the other three production factors. It is assumed that the technology in the sub production function $F\left(\cdot\right)$ can be approximated by a translog cost function. Hence the system of equations in the dairy sector consists of equations (1) and (2) for $i=L,K,E$ as well as the following output equation that summarizes the technological relationship between output of dairy products and raw milk:

$$\ln Q=\ln\alpha_{0M}+\alpha_{1M}\ln M \tag{7}$$

The specification in (7) has the advantage that returns to scale are measured using proportional variations in the production quota at the farm level. The current framework explicitly accounts for proportional changes in the production quota when computing the impact of a change in output on total costs. While predetermined quantities of milk could have been modeled using a general translog cost function as in the bakery and meat sectors, a change in processed dairy output would not have been accommodated through a proportional change in material. The specification in (7) guarantees that this condition will be respected.

3 – Data

Data on input expenditures and sales receipts come from Statistics Canada’s Annual Survey of Manufactures (ASM). The available data cover the period 1990-1999. Data were also available for the 2000-2002 period, but important modifications were made to the coverage of the ASM in 2000. First, the survey stopped collecting data on hours worked in 2000 and this constitutes an important limitation when computing a price index for labour. Second, the ASM started including in 2000 all incorporated businesses with sales of less than $30,000 in manufactured goods as well as all unincorporated manufacturers. Finally, major conceptual and methodological changes were made to the ASM which resulted in total manufacturing shipments increasing by about 8% between 1999 and 2000. The impacts of including the post-2000 data in the empirical model are largely unknown and thus it was considered preferable to exclude these three years from the sample. The data were collected by province and broken down across industry according to the North American Industry Classification System (NAICS). The industries are the bread and bakery sector (#3118), the meat sector (#3116) and the dairy sector (#3115).

Four inputs are used in the model: material, labour, energy and capital. While total expenditures for the first three inputs are available in the ASM, capital expenditures must be extracted from another dataset, Statistics Canada’s Cansim table 031-0002. The data is only available at the national level and linear regressions were used to decompose aggregate capital expenditures at the provincial level. The results of the different linear models that were used are not reported here for sake of brevity. The estimation strategy consisted in specifying a parsimonious linear equation in each sector. Capital expenditures were regressed on sales, number of workers, material expenditures and energy costs, and any combination of these variables. Each equation was used to produce predicted values of capital expenditures at the provincial level. We selected the specification that minimized the distance between the summation of the predicted capital expenditures in each province and the observed capital expenditures at the national level. This criterion coincided with the model selection outcome based on the Schwartz Bayesian Criterion. The national capital price index was applied to expenditures in all provinces due to the lack of data to proxy provincial capital price indexes.

An output price index was needed to deflate total sales receipts in order to construct an output measure. Unfortunately, the industrial price index in Cansim table 329-0038 is only available starting in 1992 and is not available at the provincial level. Hence, it was decided to use the consumer food price index in each province (Cansim table 326-0002). It is important to note that each province uses a distinct reference price in computing the price index (1997 = 100) and thus the index only accounts for variations in the time domain, and does not account for regional differences in prices. Hence, the 1995 comparative price index for selected cities across Canada was used to insert variability in the consumer food price index across provinces.

A price index for labour is computed from the ASM dataset using total wages paid to production employees divided by hours of work. Price indexes for the other two inputs must be obtained from sources other than the ASM. Because the material input mainly includes the farm output sold to manufactures, the producer price index was used to deflate material expenditures. While there is no clear-cut farm product that exactly fits the mix of raw material in each processing sector, price indexes for grain, livestock and dairy products in Statistic Canada's

Cansim database were used respectively for the bread and bakery, meat and dairy sectors. Finally, the energy price index was proxied by the electricity price index in each province. Once again, variations across provinces were computed; this time using differences in electricity prices across major cities in Canada for the year 2001 as reported by Hydro-Quebec (2001).

Tables 1, 2 and 3 present descriptive statistics of the meat, bread and bakery and dairy sectors respectively. Note that the number of available observations differs across sectors. Confidentiality issues will often result in a missing observation in the dataset. If the number of firms is not sufficiently large, the observation at the industry level is withdrawn from the database to prevent releasing information about individual firms. This leaves us with 44, 60 and 62 observations in the bread and bakery, meat and dairy sectors respectively. Material is included in table 3 although the separability assumption for the dairy technology implies that the cost share system only applies for energy, capital and labour. Still, it is interesting to compare the factor intensity in the dairy industry with the other two industries. Tables 1, 2 and 3 report the average expenditure share of each input with some information about their distribution. The minimum and maximum values give an indication of the variability in shares across years and provinces. In relative terms, the smallest variation in input expenditure shares occurs for material which is also the most important expenditure share. This has important implications on scale economies because as long as the price of material does not change with output, economies of scale will be small because total costs are dominated by material expenditures. There are some important variations in labour expenditures across observations. The greatest variation in the price index in relative terms occurs for energy. It also seems that the bakery sector is the most labour intensive of the three industries when measured in relative terms. Labour expenditures represent a much smaller percentage of overall expenditures in the meat and dairy sectors.

While tables 1, 2 and 3 provide an idea of the overall dispersion in the data, it is also interesting to investigate whether there are important differences across provinces in a given year. Figures 1, 2 and 3 present the input expenditure shares of four provinces in 1999 for the meat, bread and bakery and dairy sectors respectively. Generally, speaking there is little variation across provinces in 1999. However, the shares of capital and labour in the bread and bakery sector of New Brunswick are significantly different than their Quebec, Ontario and Alberta counterparts in Figure 2. Moreover, the difference between the material expenditure share between Nova Scotia and Alberta is relatively important.

4 – Results

The model in (1)-(2) with the restrictions in (5) and (6) is highly non-linear and maximum likelihood is used to estimate these equations. The statistics of interest are the scale elasticities in each sector across large and small provinces. Preliminary runs revealed that imposing concavity on the cost function did not yield the somewhat miraculous results of Ryan and Wales (2000) in that concavity is not respected at all observations. One explanation is perhaps that there exists greater heterogeneity across observations in the current sample than in Ryan and Wales' empirical application. They used an annual time series of U.S. output manufacturing while the current sample includes small and large provinces. The estimated parameters of the meat and bread and bakery cost functions are reported in table 4 when concavity is imposed at the 1999-Quebec observation. Table 5 presents the estimation results of the dairy cost function at the same normalization point.

A Likelihood Ratio (LR) test was used to determine if a trend needed to be included in the model. The LR statistic is: $LR = 2\left[\ln\left(L_U\right) - \ln\left(L_R\right)\right]$; where L_U and L_R denote the value of the likelihood function for the unrestricted and restricted $\left(\alpha_t = \alpha_{tt} = \alpha_{it} = \alpha_{tQ} = 0; \forall i\right)$ models respectively. It follows a chi-squared distribution with 6 degrees of freedom. The LR statistic in table 4 for the bread and bakery sector is 40.92 and yields a *p-value* less than 0.01 for the null hypothesis that the trend coefficients are jointly not significant. Similar results hold for the meat and dairy sectors. While the general fit of the empirical models seems adequate, it is difficult to interpret the parameters as stand-alone meaningful economic statistics.[2] For this purpose, the notion of input substitutability and scale elasticities are introduced.

Blackorby and Russel (1989) argue that the notion of Hicksian substitutability among inputs should be measured by the Morishima elasticities of substitution. The Morishima elasticity (denoted by M_{ij}) is computed as the derivative of the relative input use in logarithmic form, $\ln\left(x_i / x_j\right)$, with respect to the logarithmic of the price ratio p_i / p_j. It is equal to (Wohlgenant, 2001): $M_{ij} = \varepsilon_{ij} - \varepsilon_{jj}$; where ε_{ij} is the price elasticity of the demand for the i^{th} input with respect to the price of the j^{th} input. The Morishima elasticities are data dependent; but when evaluated at the normalization point, the uncompensated elasticities are strictly function of the parameters: $\varepsilon_{ij} = \left(\alpha_{ij} - \delta_{ij}\alpha_i + \alpha_i\alpha_j\right) / \alpha_i\alpha_j$; where $\delta_{ij} = 1$ if $i = j$ and zero otherwise.

The Morishima elasticities for the meat sector using the 1999-Quebec observation as the normalization point are presented in table 6. While elasticities can differ across provinces and time, unreported results suggest that they are rarely significantly different from a qualitative standpoint. A particularly interesting elasticity is the change in the ratio of material to another input following a change in the price of that other input. The substitution possibilities between material and capital and material and energy do not seem to be negligible. For example, a one percent decrease in the price of energy will decrease the ratio of materials to energy usage by

0.73 percent. Similarly, a decrease of 1% in the price of capital will decrease the ratio of material to capital by 0.41 percent. Substitution seems to be more limited between material and labour.

Morishima elasticities in table 7 document substitution possibilities between all four inputs for the bread and bakery sector. The results are strikingly different than substitution elasticities for the meat sector. The ratio of material to labour is very price responsive with an elasticity of 1. There is no substitution between material and capital as the point estimate of elasticity is 0.01. As in the case of labour, the ratio of material to energy is quite elastic. The most significant substitution effects involve energy as the Morishima elasticities are greater than one. Morishima elasticities for the dairy sector are presented in table 8. By construction there are no substitution possibilities between material and other inputs. As mentioned before, this rather restrictive assumption was built in the model to account for the supply management policy. The substitution elasticities between capital and energy are non negligible while there is less substitution between labour and capital or energy.

Because all normalized data points equal one, it is relatively straightforward to compute returns to scale evaluated at the normalization point given the logarithmic form of the cost function. The scale elasticity in the meat and bread and bakery sectors are equal to the derivative of the cost function with respect to output; and thus are directly measured by the parameter α_Q. A scale elasticity greater (lower) than one indicate decreasing (increasing) returns to scale. Standard inference can be carried out in the usual way using asymptotic theory. Computing scale elasticities in the dairy industry is however more involved because of the perfect complementarity between material and the other inputs. The cost function is first divided up into two sub cost-functions: one applies to expenditures in material while the second measures expenditures in energy, capital and labour and has the translog form defined in (1). The sub-cost function for material is: $\ln C_M = \alpha_{1M}^{-1} \ln\left(\alpha_{0M}^{-1}\right) + \ln p_M + \alpha_{1M}^{-1} \ln Q$. Hence the scale elasticity associated with expenditures in material is measured by α_{1M}^{-1} while the scale elasticity of the translog sub cost function is measured by α_Q. Obviously, the total scale elasticity is not the sum of the two separate elasticity measures. The following procedure is used to compute the total scale elasticity: 1) compute fitted costs associated with each sub-cost function; 2) compute the cost changes following a one percent change in output using the sub-cost scale elasticities (α_Q and α_{1M}^{-1}); and 3) add up the predicted change in the two sub-costs and compare them to the initial fitted costs in step 1.

Tables 9, 10 and 11 present the elasticities of scale of different provinces in 1999 for the meat, bread and bakery and dairy sectors respectively. As mentioned before, concavity can only be imposed locally if one wishes to preserve the flexibility of the cost function. To make sure that the reported elasticity are consistent with the concavity property of the cost function being verified, the model is re-estimated using each observation in the tables as a different normalization point. While this procedure is lengthy, it has the advantage of being consistent with the bootstrap procedure that is used below. Imposing concavity locally for the province of Quebec in a given year may well result in concavity being verified for other provinces in many different years; however, there is no guarantee that the non-violation of concavity will be replicated in bootstrap samples. The only way to do so is to use a different normalization point for the four reported cases when calculating the elasticities such that the bootstrap samples also satisfy the concavity property.

Asymptotic confidence intervals are reported for the meat and bakery sectors. The asymptotic distribution of the scale elasticity in the dairy sector is largely unknown because this statistic involves many computations[3] and thus bootstrap techniques were used. Moreover, it is well known that the bootstrap distribution of a statistic provides a better estimate of the finite sample distribution of the statistic than the asymptotic distribution if the statistic is asymptotically pivotal (Horowitz, 2001).[4] This may be especially true in the current context given the relatively short samples. For the meat and bread and bakery sectors, the scale elasticity parameters are not asymptotically pivotal because their distribution, although asymptotically normal, depends on unknown population mean and variance parameters. The scale elasticity in the dairy sector is also not pivotal because it is a combination of many parameters.

Beran (1987) has shown that the double bootstrap improves the accuracy of a single bootstrap when an asymptotically pivotal statistic[5] is not available by estimating a coverage error for a confidence interval and then uses this estimate to adjust the single bootstrap thus reducing its error. The double bootstrap method is relatively easy to implement and McCullough and Vinod (1998) provide an excellent description of the algorithm that needs to be implemented. In summary, let the initial maximum likelihood parameters be represented by the vector $\hat{\boldsymbol{\theta}}$ and the predicted dependent variables by the matrix $\hat{\mathbf{Y}}$. Moreover, let the centered and rescaled sample residuals be denoted by $\hat{\boldsymbol{\varepsilon}}$. Form a pseudo matrix of dependent variables $\mathbf{Y}^*$ by sampling with replacement from the matrix $\hat{\boldsymbol{\varepsilon}}$ a matrix $\boldsymbol{\varepsilon}^*$ such that $\mathbf{Y}^* = \hat{\mathbf{Y}} + \boldsymbol{\varepsilon}^*$. A bootstrap estimate of the parameter of interest is obtained through maximum likelihood and is denoted $\boldsymbol{\theta}_j^*$. Repeat this procedure J times.

For each bootstrap sample, the centered and rescaled residuals ε^* are used to form a second bootstrap sample $\mathbf{Y}^{**} = \mathbf{Y}^* + \boldsymbol{\varepsilon}^{**}$. The model in (1)-(2) with restrictions in (5) and (6) is re-estimated to obtain the vector of parameters $\boldsymbol{\theta}_{jk}^{**}$. This procedure is repeated K times. Compute the pivotal statistic $Z_j = \#\left(\boldsymbol{\theta}^{**}_{jk} < \hat{\boldsymbol{\theta}}\right)\big/K$. The idea is that under fairly general conditions, the statistic Z_j is uniformally distributed asymptotically (and thus is an asymptotically pivotal statistic). Once all bootstrap samples are obtained, the statistics $\boldsymbol{\theta}^*_j$ and Z_j can be ordered according to $\boldsymbol{\theta}^*_{(1)}$, $\boldsymbol{\theta}^*_{(2)}$, …, $\boldsymbol{\theta}^*_{(J)}$ and $Z_{(1)}$, $Z_{(2)}$, …, $Z_{(J)}$. The simple bootstrap $\alpha\%-$confidence interval is $\left[\theta^*_{((J+1)(1-\alpha))}, \theta^*_{((J+1)\alpha)}\right]$. The double bootstrap interval is $\left[\theta^*_{((J+1)\alpha_L)}, \theta^*_{((J+1)\alpha_U)}\right]$ where $\alpha_L = Z_{((J+1)(1-\alpha))}$ and $\alpha_U = Z_{((J+1)\alpha)}$. Hence, the role of the statistic Z is to redefine the appropriate upper and lower bounds for the confidence intervals.

Table 9 suggests that there are increasing returns to scale in the meat sector because the point estimate for all four provinces is below one. Hence, increasing industry output should lower the industry's average costs. Unfortunately, the asymptotic theory and bootstrap inference do not rule out decreasing returns to scale as the upper bound of the 95% confidence interval is greater than one. The single bootstrap interval does not seem different than the asymptotic confidence interval. While the double bootstrap does not significantly change the conclusions of the other two methods, it does provide some refinements to the confidence interval. It is interesting to note that there is no statistically significant difference between the scale elasticities in each province despite that production levels are quite different.

Table 10 presents the scale elasticities in the bread and bakery sector of Quebec, Alberta, Ontario and New Brunswick. The asymptotic coverage for the scale elasticity parameter is different than the coverage offered by the single percentile bootstrap method in the four provinces. There exist significant returns to scale in the two smaller provinces (Alberta and New Brunswick). The point estimate of the scale elasticity in Alberta suggests that a one percent increase in output in 1999 would generate a 0.87 percent increase in total costs for the industry.

There exists decreasing returns to scale at the industry level for the sector in Ontario. While increasing returns to scale in the Quebec industry cannot be ruled out from a statistical point, the confidence interval is skewed to the right around the cut-off value of one; suggesting that the industry cannot lower average costs by increasing output.

Table 11 provides the scale elasticity parameters for the dairy industry. The point estimate for New Brunswick in 1999 is 0.93 which is statistically lower than one at the 95 percent confidence level both asymptotically and using the bootstrap inference. Hence, an increase in output of 1% would only increase total costs in the industry by 0.93%. Note that this increase in output must necessarily be accompanied by a proportional increase in material according to the technology specification. In other words, dairy processors cannot increase output without a corresponding increase in the production quota at the farm level. Hence, the evidence suggests that the dairy processing industry in that province could move down its average cost function by increasing output would milk production at the farm level be set accordingly. The point estimate of the scale elasticity is however greater than one for the two largest producing provinces, Quebec and Ontario. This suggests that increasing output at the farm level would lead to increases in the industry average costs. It must be noted that these conclusions hold in the context of 1999 and thus abstract from any potential structural change in the industry (mergers, acquisitions, etc.) that has occurred since.

5 – Conclusion

Broad globalization forces in the agri-food sector are pressuring agri-food firms to increase their competitiveness. In some instances, trade liberalization offers opportunities to expand output while import competing agri-food industries may be forced in other instances to cut back production. In any case, concentration and output expansion/contraction do affect the cost structure of individual firms and the overall industry. The objective of the paper is to measure potential (dis)economies of scale in the Canadian agri-food manufacturing sector. There has been a considerable literature documenting economies of scale in U.S. agri-food industries but no attention has been devoted to Canadian industries. U.S. and Canadian firms compete in common markets and most likely share many similarities from a technological perspective. However, the existence of supply management at the Canadian farm level and potential differences in factor prices can lead to substantial differences in the overall cost structure of Canadian and U.S. food processing firms.

Cost functions for three Canadian manufacturing agri-food sectors (meat, bakery and dairy) are estimated using provincial data from 1990 to 1999. The Christensen, Jorgensen and Lau (1973) translog flexible functional form is used. The concavity property of the cost function is imposed locally using the approach of Ryan and Wales (2000). The Morishima substitution elasticities in the bakery sector indicate that substitution possibilities between material and energy and material and labour are important. Conversely, substitution possibilities between the farm input and the other inputs in the meat sector are less significant. To account for the implications of supply management on the cost structure of dairy processing firms, strong separability between material and the other inputs was introduced through a Leontief technology which yields two sub-cost functions that are estimated jointly. The sub-cost function for expenditures in milk is log-linear while the sub-cost function for expenditures on capital, labour and energy has the translog form. This rather stringent assumption on the technology was introduced to account for the exogenous supply of milk at the farm level and more importantly to restrict changes in processed dairy products to be accompanied by proportional changes in the supply of raw milk at the farm level.

Inference is carried out using the usual asymptotic theory as well as bootstrap inference. In particular, the ability of the double bootstrap to provide refinements in inference is investigated. The idea of the double bootstrap is to sample from the initial bootstrap sample in order to form an asymptotically pivotal statistic. This statistic is used to correct the inference generated by the initial bootstrap sample. Scale elasticity parameters indicate that increasing returns to scale are present in small bakery industries. Point estimates suggest that increasing returns to scale exist at the industry level in the meat sector, but statistical inference cannot rule the existence of decreasing returns to scale. Moreover, there are no statistical differences in the measure of returns to scale across provinces. Finally, there exists evidence of increasing returns to scale at the industry level in the dairy industries of Alberta and New Brunswick. The scale elasticity for the two largest provinces (Ontario and Quebec) is greater than one, but inference does not reject the null hypothesis of increasing returns to scale. The bootstrap method is particularly helpful to compute confidence intervals in the dairy sector because the asymptotic theory is practically difficult to compute in that case.

The major limitation of the study is the impossibility to distinguish the source of returns to scale in the dataset. The provincial data yields elasticities of scale at the industry level that encompass plant-level and firm-level economies of scale as well as economies of scale external to firms. Future research endeavours should focus on breaking the data limitation barriers and investigate with firm level data the cost structure of Canadian food processors. In that case, meaningful comparisons could be drawn with the U.S. industry.

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Table 1. Summary statistics for the meat sector

Variables	Average	Standard deviation	Minimum	Maximum
Expenditure shares				
Material	0.84	0.032	0.78	0.94
Capital	0.02	0.005	0.01	0.03
Energy	0.02	0.004	0.01	0.02
Labour	0.13	0.026	0.05	0.17
Prices				
Material	101.65	7.02	84.23	115.41
Capital	99.38	4.08	94.12	105.21
Energy	108.93	25.56	71.24	165.88
Labour	96.46	5.47	86.31	112.29
Output	17533.10	15569.21	1423.60	43509.51

Table 2. Summary statistics for the bread and bakery sector

Variables	Average	Standard deviation	Minimum	Maximum
Expenditure shares				
Material	0.59	0.044	0.52	0.671
Capital	0.09	0.043	0.05	0.193
Energy	0.03	0.005	0.02	0.044
Labour	0.29	0.047	0.17	0.373
Prices				
Material	104.32	20.31	72.64	175.37
Capital	95.37	3.73	88.91	100.00
Energy	114.18	22.14	77.35	162.94
Labour	92.76	9.26	73.84	106.27
Output	7625.60	7438.81	531.31	21815.02

Table 3. Summary statistics for the dairy sector

Variables	Average	Standard deviation	Minimum	Maximum
Expenditure shares				
Material	0.86	0.029	0.79	0.91
Capital	0.05	0.026	0.02	0.12
Energy	0.02	0.006	0.01	0.03
Labour	0.07	0.014	0.05	0.11
Prices				
Material				
Capital	105.74	4.44	100.00	112.54
Energy	126.97	31.68	74.1	197.36
Labour	100.45	20.58	66.43	151.03
Output	9816.70	11469.05	703.19	33854.01

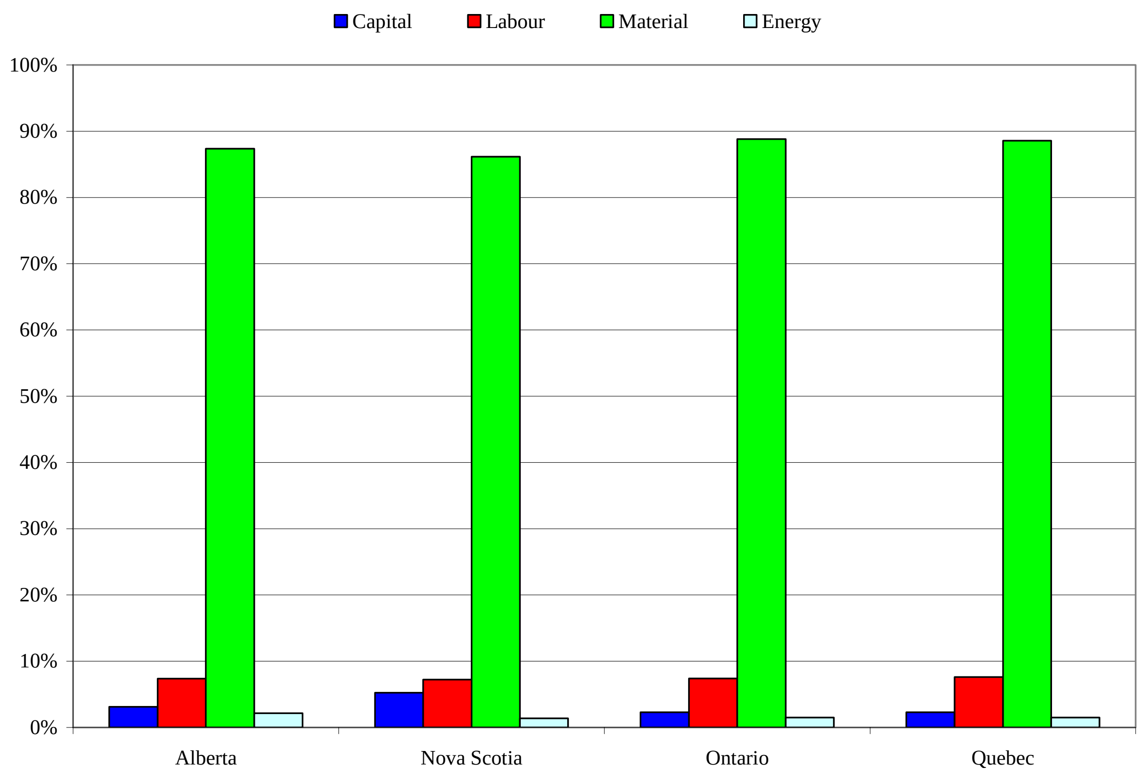

Figure 1. Expenditure shares in the meat processing industry of four Canadian provinces

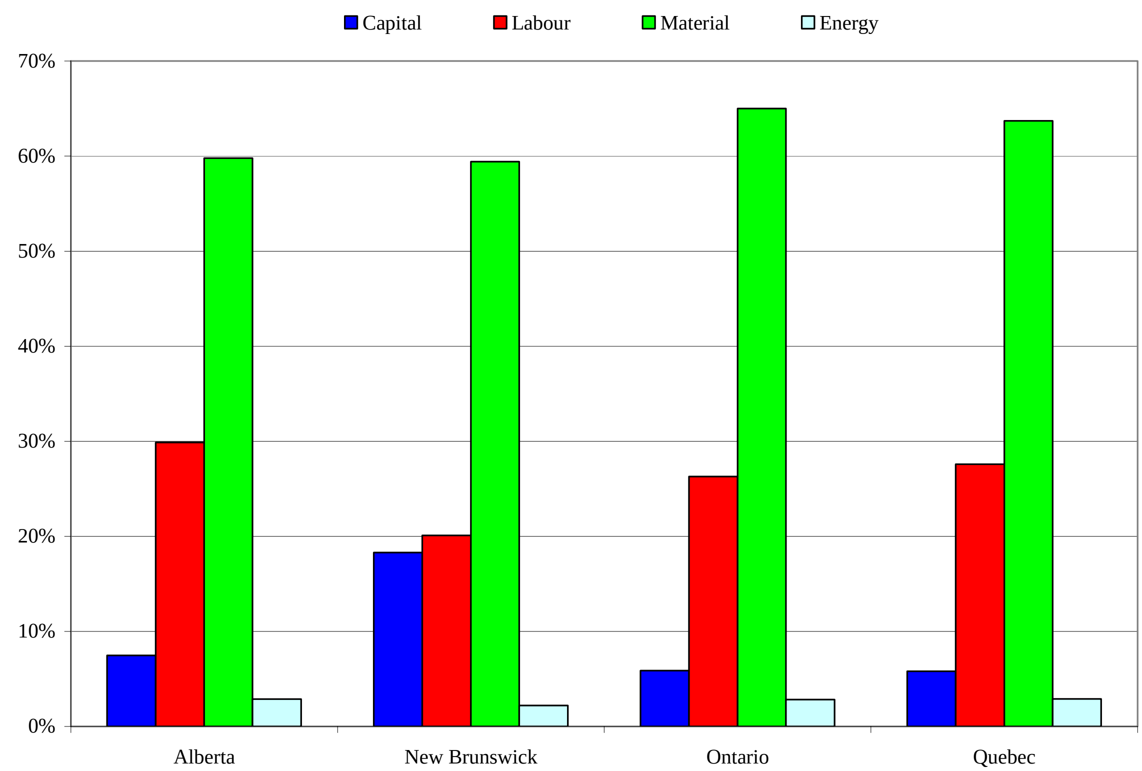

Figure 2. Expenditure shares in the bread and bakery industry of four Canadian provinces

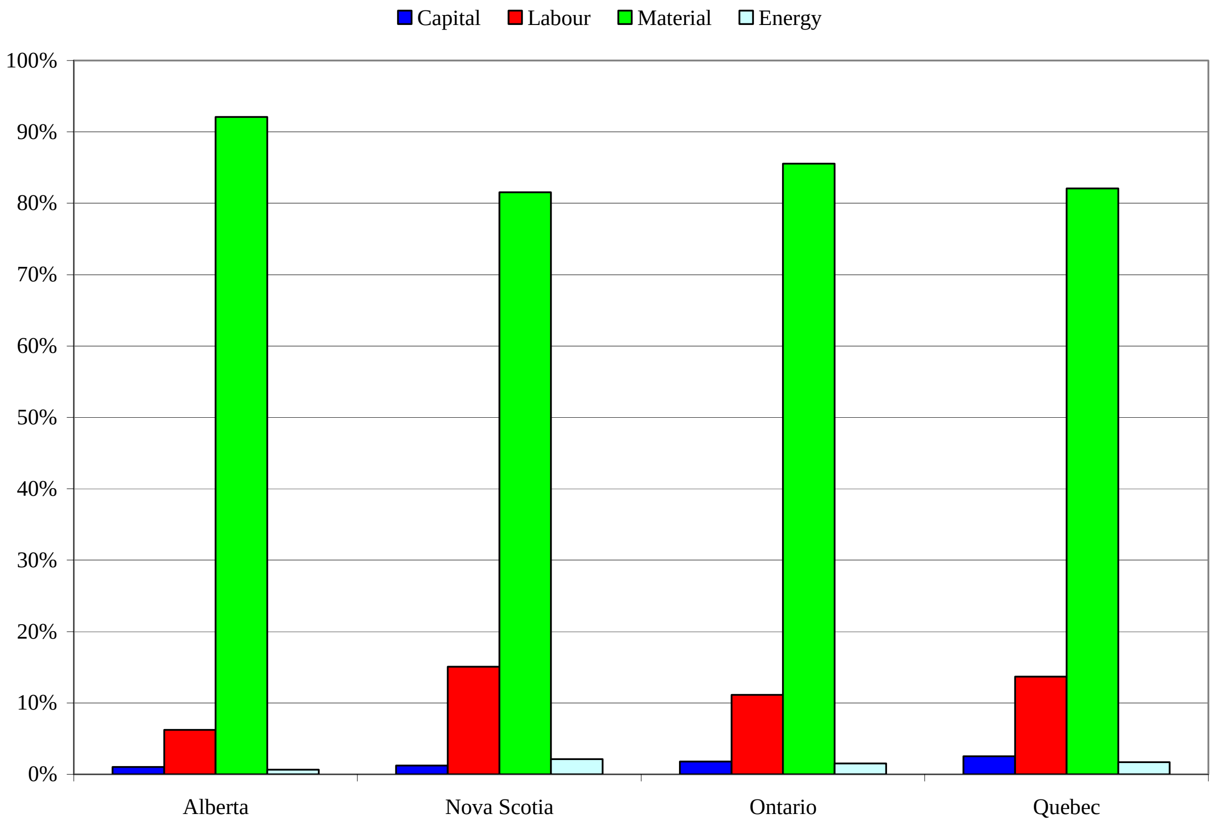

Figure 3. Expenditure shares in the dairy processing industry of four Canadian provinces

Table 4. Coefficients of the translog cost function for the meat and bread and bakery sectors

	Meat		Bread and bakery	
Coefficients	Estimate	Standard error	Estimate	Standard error
α_0	13.30	0.0621	14.809	0.0169
α_1	0.099	0.0082	0.022	0.0010
α_2	0.258	0.0016	0.117	0.0051
α_3	0.611	0.0014	0.847	0.0065
α_Q	1.050	0.0271	0.968	0.0196
α_{QQ}	0.125	0.0149	0.0052	0.0148
α_{1Q}	-0.020	0.0034	0.0019	0.0004
α_{2Q}	0.005	0.0054	-0.0137	0.0023
α_{3Q}	0.021	0.0035	0.0134	0.0029
α_t	-0.008	0.0134	-0.0027	0.0062
α_{tt}	0.003	0.0015	0.0007	0.0012
α_{1t}	0.0046	0.0014	0.0004	0.0001
α_{2t}	-0.0062	0.0023	0.0012	0.0009
α_{3t}	0.0025	0.0017	-0.0019	0.0011
α_{Qt}	-0.0010	0.0016	-0.0068	0.0013
δ_{11}	0.0640	0.0225	-0.0951	0.0201
δ_{12}	-0.1564	0.1417	0.1450	0.0279
δ_{13}	0.2663	0.1048	0.0125	0.0386
δ_{22}	0.4088	0.0551	-0.0811	0.0679
δ_{23}	-0.2918	0.1111	0.15976	0.0629
δ_{33}	0.0000	0.0168	-0.0000	0.1036
Likelihood ratio test	Statistic	*p*-value	Statistic	*p*-value
$H_0 : \alpha_t = \alpha_{tt} = \alpha_{1t} = \alpha_{2t} = \alpha_{3t} = \alpha_{Qt} = 0$	39.16	0.000	40.92	0.000

Table 5. Coefficients of the translog cost function for the dairy sector

Coefficient	Estimate	Standard error
α_0	12.66	0.0354
α_1	0.173	0.0130
α_2	0.698	0.0125
α_Q	1.210	0.0201
α_{QQ}	0.226	0.0083
α_{1Q}	-0.0751	0.0054
α_{2Q}	0.0725	0.0054
α_t	-0.0068	0.0069
α_{tt}	-0.0010	0.0012
α_{1t}	0.0019	0.0024
α_{2t}	-0.0021	0.0021
α_{Qt}	0.0038	0.0014
δ_{11}	0.2111	0.0279
δ_{12}	0.0951	0.0411
δ_{22}	0.0000	0.2388
α_{0M}	0.2785	0.0839
α_{1M}	1.0073	0.0102
Likelihood ratio test	Statistic	*p*-value
$H_0 : \alpha_t = \alpha_{tt} = \alpha_{1t}$ $= \alpha_{2t} = \alpha_{Qt} = 0$	18.80	0.002

Table 6. Morishima input price elasticities in the meat sector

Quantity ratio (numerator)	Price change			
	Capital	Labour	Material	Energy
Capital		0.86	0.08	0.44
Labour	0.53		0.13	0.73
Material	0.41	0.25		0.73
Energy	0.07	0.42	0.97	

Table 7. Morishima input price elasticities in the bread and bakery sector

Quantity ratio (numerator)	Price change			
	Capital	Labour	Material	Energy
Capital		0.84	0.08	1.48
Labour	0.08		0.88	1.44
Material	0.01	1.01		1.38
Energy	0.39	1.38	0.63	

Table 8. Morishima input price elasticities in the dairy sector

Quantity ratio (numerator)	Price change		
	Capital	Labour	Energy
Capital		-0.101	1.107
Labour	0.237		0.769
Energy	0.775	0.230	

Table 9. Scale elasticities in the meat sector

Province	Elasticity point estimate	Asymptotic		Single bootstrap		Double bootstrap	
		Lower	Upper	Lower	Upper	Lower	Upper
Quebec	0.97	0.93	1.01	0.93	1.01	0.94	1.00
Ontario	0.97	0.92	1.02	0.92	1.01	0.92	1.01
Alberta	0.97	0.93	1.02	0.93	1.02	0.92	1.01
Nova Scotia	0.96	0.91	1.01	0.91	1.01	0.91	1.00

Table 10. Scale elasticities in the bread and bakery sector

Province	Elasticity point estimate	Asymptotic		Single bootstrap		Double bootstrap	
		Lower	Upper	Lower	Upper	Lower	Upper
Quebec	1.05	1.00	1.11	0.97	1.11	0.99	1.11
Ontario	1.12	1.06	1.18	1.03	1.19	1.06	1.19
Alberta	0.87	0.82	0.92	0.80	0.94	0.81	0.92
New Brunswick	0.78	0.72	0.83	0.71	0.85	0.72	0.83

Table 11. Scale elasticities in the dairy sector

Province	Elasticity point estimate	Single bootstrap		Double bootstrap	
		Lower	Upper	Lower	Upper
Quebec	1.01	0.99	1.04	0.97	1.05
Ontario	1.01	0.98	1.03	0.97	1.06
Alberta	0.97	0.94	0.99	0.93	1.01
New Brunswick	0.93	0.91	0.96	0.89	0.96

Endnotes

[1] Another approach would be to use a cost function which is globally concave and flexible (such as in Kumbhakar, 1992). However, it generally involves a large number of parameters to be estimated and the small number of observations in the present context makes this alternative unattractive.

[2] Input regularity conditions (*i.e.* predicted factor shares greater than zero) were found to be satisfied in all cases for the three industries. The output regularity condition (predicted marginal cost greater than zero) was satisfied in a large proportion of cases as well.

[3] The delta method (Greene, 2003) was considered to compute the asymptotic distribution of the dairy scale elasticity but was dropped because it generated excessively large confidence intervals.

[4] Asymptotically pivotal statistics are statistics whose asymptotic distribution does not depend on unknown population parameters (*e.g.*, the standard normal and chi-squared distributions).

[5] Even when an asymptotically pivotal statistic exists, double bootstrap methods have a higher order of accuracy (McCullough and Vinod, 1998).