

Measuring Efficiency in Fruit and Vegetable Marketing Co-operatives with Heterogeneous Technologies in Canada

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*Selected Paper prepared for presentation at the American Agricultural
Economics Association Annual Meeting, Providence, Rhode Island,
July 24-27, 2005*

Authors acknowledge the financial support of the Co-operative Program in Agricultural Marketing and Business, Department of Rural Economy, University of Alberta

Introduction

The development of efficiency measurement and analysis dates back more than five decades (Debreu 1951; Koopmans 1951; Shephard 1953; Farrell 1957; Solow 1957) with major theoretical and empirical efficiency research advancements occurring in the late 1970's (Aigner, Lovell, and Schmidt 1977; Battese and Corra 1977; Meeusen and den Broeck 1977; Charnes, Cooper, and Rhodes 1978). Since then there have been an increasing number of applications of efficiency analyses across diverse industries and organizational structures. Yet, the applications of efficiency analysis to the agribusiness co-operative sector remain limited, particularly in the fruit and vegetable co-operatives.

Information concerning the level of productive efficiency within the co-operative sector is potentially important because of the ongoing changes that are affecting performance within that sector; increased competition arising from globalization and deregulation, capital constraints, and increased industry concentration. These changes will lead to more market-oriented food manufacturing but they may result in competitive pressure being placed on Canadian food processors. The Canadian food manufacturing sector has had to overcome these challenges in order to stay competitive in both the Canadian and international markets. In the case of co-operatives, "how have agribusiness co-operatives adapted in order to meet these challenges?" One way by which the growth and competitiveness of the co-operative sector can be achieved is through improvement in efficiency/productivity, and this may be achieved by rationalizing production costs.

Improvement in efficiency may be crucial as changes in regulation, technology and other market developments reduce the competitive advantage enjoyed by co-operative businesses, and bring into question their long term viability. The implication is that inefficient co-operatives will exit from the industry in a competitive market, but efficient co-operatives will not. Put differently, as long as co-operative firms are not insulated from competition by mechanisms such as regulation and subsidy, inefficient co-operatives may be unable to continue to survive in the long run, as is true for their investor owned counterparts. Thus, the enhanced level of competitive rivalry may force co-operatives into adopting low cost and price strategies.

The fruit and vegetable industry is part of a complex and integrated network of agricultural enterprises associated with the production, transportation, processing, and shipment of fruit and vegetable products. As these products progress through these different market channels, value is added from labour, capital, and management. These contributions have a significant impact on the economy. For example, the value of all Canadian fruit, including apples, tree fruit and berries, amounted to \$517.1 million in 2002. Within the overall fruit category, the berry sector accounted for the largest percentage of value with 54.5 percent, followed by apples with 31.2 percent, and tree fruits with 14.1 percent.

Over the years, agricultural co-operative have played a major role in the fruit and vegetable industry of Canada. Fruit and vegetable marketing co-operatives are involved in processing and value added activities. In 2002, fruit and vegetable co-operatives marketed over CAN \$223.5 million in Canada and abroad. However, the fruit and vegetable industry has shown a decline in their market share over time. For example, in 2002 the market share of fruit and vegetable co-operatives was 6 percent as compared to 23 percent in 1998 (Canadian Co-operative Secretariat, 2004) (Figure 1). This reduction in the market share might be due to the loss of some of the fruit and vegetable co-operatives. The number of reporting fruit and vegetable co-operatives declined from 39 in 1998 to 30 in 2001. If this trend continues, it might be the case that a further reduction in the number of fruit and vegetable co-operatives can be expected. As mentioned previously, the survival of fruit and vegetable co-operatives hinges upon their competitiveness with domestic and global investor owned firms, and their long run competitiveness depends upon low cost of production or their efficiency of resource use.

Efficiency of resource allocation in the economic literature related to the co-operative sector is a controversial issue. Several attempts have been reported in the literature to measure performance of the agribusiness co-operative sector and credit unions (Ferrier and Porter 1991; Caputo and Lynch 1993; Ariyantne et al. 1997; Berry 1994; Sexton and Iskow 1993; Akridge and Hertel 1992; Evans and Guthrie 2002; Thraen, Hahn, and Roof 1987; Singh, Coelli, and Fleming 2001; Lavado 2004; Esho 2001; Ariyaratne et al. 2000; Lang and Welzel 1999; Fukuyama, Guerra, and Weber 1999; Gorton and Schmid 1999; Worthington 1999; Brown, Brown, and O'Connor 1999; Worthington 1998; Worthington 1998; Zou 1992; Stutzman and Stansell 1992; Defourny, Lovell, and N'gbo 1992). Empirical firm efficiency studies can play a prominent role in providing useful information for a variety of groups. Measurement of efficiency scores is helpful to assess the relative performance of firms. Firm efficiency information can then be used by managers, co-operative members, regulators, directors and policymakers. However, to date no efficiency studies have been undertaken for the Canadian fruit and vegetable industry in general and fruit and vegetable co-operatives in particular.

Furthermore, although the notion of efficiency is one of the most commonly used tools in evaluating performance of firms within the agricultural and food markets, the literature investigating the association between cost efficiency and financial leverage is limited. Co-operative agribusiness firms face more difficulties in raising the capital necessary to finance capital investments because of capital constraints/structure (Doyon, 2001). One of the major issues concerning co-operative finance is the influence of debt leverage on co-operative performance. Theoretically, leverage increases the pressure on managers to perform, because it reduces the moral hazard behaviour by reducing “free cash flow” at the disposal of managers (Jensen, 1986). This suggests a positive relationship between leverage and efficiency. On the other hand, higher leverage may raise agency costs of debt because of the conflicting interests between co-operative shareholders/members and debtholders, resulting in a negative relationship between leverage and efficiency (Jensen and Meckling, 1976; Myers, 1977). The theoretical literature therefore provides mixed results regarding the relationship between financial leverage and firm performance. A study of the relationship between financial leverage and performance may provide empirical insights about the impact of capital structure on the competitiveness of co-operative firms.

The objectives of this study are to estimate the efficiency of fruit and vegetable co-operatives in Canada and to investigate the relationship between the degree of financial leverage and efficiency. The contributions of this study are in (i) determining the cost structure of Canadian fruit and vegetable marketing co-operatives and measuring efficiency scores that take into account unobserved technological difference across firms; and (ii) testing the influence of financial leverage and firm size on efficiency.

Efficiency Measurement

In economics, the term “efficiency” is commonly used in a variety of settings (e.g., efficient prices, efficient markets, efficient firms). Generally speaking, economic efficiency refers to scarce resources being used in an optimal fashion. Within production economics, the term efficiency is defined in terms of a firm’s ability to convert inputs into outputs and respond optimally to economic signals (i.e., prices). This section provides a brief review of efficiency concepts and measures as they relate to firm production decisions.

Measuring efficiency of a firm is important from both a theoretical and a policy point of view. From an empirical perspective, a policymaker’s interest may lie in knowing how far a given firm can increase its output, without using further resources, by increasing efficiency. From a theoretical perspective, interest lies in developing an appropriate measure of efficiency and studying its properties. A great number of studies have been devoted to theoretical development of the relative efficiency measurement of economic units over the past few decades.

Farrell (1957) proposed a framework to quantify efficiency measures based on the concept of a production frontier. A production frontier is defined as the maximum output that can be obtained from a specified set of inputs, given the existing technology available to the firms (Forsund et al., 1980). The concept of a production frontier is consistent with the “standard” representation of technology; specifically, a production function. Deviations from a production frontier can be interpreted as a measure of inefficiency from a technical perspective. If the output of the firm lies below the frontier, it is regarded as inefficient.

The degree to which a firm is “off” the production frontier is an indication of technical efficiency. According to Färe et al. (1985: pp. 3-4) a producer is said to be technically efficient if production occurs on the boundary of the producer's production possibilities set, and technically inefficient if production occurs on the interior of the production possibilities set. Alternatively, a firm is technically efficient if an increase in any output requires a reduction in at least one other output or an increase in at least one input (Koopmans, 1951).

A second type of efficiency, as it relates to firm production, is allocative efficiency. Allocative (or price) efficiency refers to the proper (or improper) choice of input combinations, given economic signals. A producer is said to be allocatively efficient if production occurs in a subset of the economic region of the production possibilities set that satisfies the producer's behavioural objective. The location of this subset is determined by the prices faced by the producer and the producer's behavioural goals. Allocative efficiency is measured relative to the efficient production function as the ratio of “optimal” input proportions to the input proportions actually used (French, 1977). A technically efficient producer may be allocatively inefficient if production occurs at the wrong point on the boundary of the economic region of the production possibilities set, where “wrong” is in relation to prices faced by the producer and the producer’s behavioural goal.

Technical and allocative efficiency, taken together, contribute to the overall economic efficiency for the firm. If the firm is producing on the production frontier, using the optimal proportions of inputs given relative prices and the firm’s behavioural goal, the firm is said to be economically efficient. Economic inefficiency may occur through one or both of technical inefficiency and allocative inefficiency, as defined above. The product of the index of technical efficiency and the index of allocative efficiency is a measure of economic efficiency of the firm. A firm that is efficient both technically and allocatively has an economic efficiency index of 1.0 (Farrell, 1957).

As stated above, allocative and economic efficiency both require an economic behavioural assumption (e.g., an objective of profit or revenue maximization, or cost minimization). One of the fundamental decisions in measuring efficiency is the choice of concept to use. The two most important economic efficiency concepts that are based on production economic decision making are cost and profit efficiencies. Economic efficiency based on a profit function measures how close a co-operative is to producing the maximum possible profit given a particular level of input prices and output prices. On the other hand, economic efficiency based on a cost function provides a measure of how close a co-operative’s cost is to what a best-practice co-operative’s cost would be for producing the same output bundle under the same conditions.

The two approaches differ in terms of some fundamental assumptions. The profit function is specified in terms of variable profits instead of variable costs and takes output prices as given, as opposed to holding output quantities fixed as is the case with the cost function.

Assuming that the level of co-operative processor output is given, the profit or the welfare maximization problem for the co-operative is equivalent to minimizing the short-run total cost function, and hence, the cost function approach may be an appropriate efficiency concept. Therefore, this study focuses on cost minimising behaviour of co-operative firms. In this regard, cost efficiency is an appropriate measure of economic efficiency. Cost efficiency is an economic efficiency associated with

the input oriented technical efficiency measure (i.e. output is held constant) (Kumbhakar and Lovell, 2000). As such, cost efficiency is defined as the ratio of the minimum cost of producing the output for the firm in question, assuming complete technical and allocative efficiency, to the actual cost at given input prices and technology.

Using the standard cost function, $C(y; w) = \text{Min}\{x \cdot w \mid x \in L(y)\}$, cost efficiency can be defined as: $CE(x, y; w) := \frac{C(y; w)}{x \cdot w}$ ¹. The measure of input allocative efficiency is given by a function:

$AE_1 = \frac{CE(y, x; w)}{TE_1(y, x)}$, where $TE_1(\cdot)$ is a measure of input oriented-technical efficiency, defined as:

$TE_1 = [D_1(y, x)]^{-1}$, and $D_1(y, x)$ is an input distance function. From the above, allocative efficiency can be seen as the cost efficiency measure (or overall economic efficiency in general) applied to the technically efficient reference production plan. The measure of cost efficiency is bounded between zero and unity, and achieves its upper bound if and only if a producer uses a cost-minimizing input vector.

Stochastic Frontier Model

The empirical results of efficiency analysis depend on the approach that is used and on the assumptions imposed under a particular approach. Two major approaches have been developed for measuring efficiency: the mathematical programming approach commonly referred to as Data Envelopment Analysis or DEA, and the econometric approach. Both methods involve estimation of “best practice” frontiers, with the efficiency of a specific decision making unit measured relative to the frontier.

The econometric approach involves specification of a functional form for production, cost, revenue, or profit (Kumbhakar and Lovell, 2000). The methodology is stochastic; firms can deviate from the frontier because they are inefficient or because of random shocks or measurement errors that have nothing to do with efficiency. Thus, the error term associated with the frontier function is hypothesized to consist of an efficiency component and a purely random component. Efficiency is measured by separating the efficiency component from the overall error term. Some variants of the econometric approach require that specific distributional assumptions be imposed on the components of the error terms, while others do not require distributional assumptions. By contrast, the mathematical programming approach places less structure on the frontier and is non-stochastic; that is, any departure from the frontier is measured as inefficiency.

The choice of estimation methodology has been controversial, with some researchers preferring the econometric approach (e.g., Bauer, 1990; Berger, 1993); and others the mathematical programming approach (e.g., Seiford and Thrall, 1990). The econometric approach has been criticized for having the potential to confound estimates of efficiency with specification errors. Mathematical programming, on the other hand, is non-parametric and thus less susceptible to specification errors but does not allow decision-making units to deviate from the frontier due to purely random shocks. This magnifies the impact of outliers on resulting efficiency estimates. Advocates of the econometric approach disagree about whether distributional assumptions should be imposed on the error term and, if so, which distributions are most appropriate. Some recent mathematical programming papers have criticized the prevailing DEA technique and propose instead the free disposal hull (FDH) methodology, arguing that the FDH involves fewer arbitrary assumptions and provides a better fit to the data (e.g., Tulkens, 1993).

¹ Efficiency is generally defined relative to the best-practice observed in the industry, rather than any true minimum costs, since the underlying technology is unknown.

The analysis in this study is based on efficient frontier methodology developed by Aigner et al. (1977) and Meeusen and van den Broeck (1977). The approach is stochastic and the observations may deviate from the frontier because they are inefficient or because of random shocks or measurement errors. The conceptual framework of the stochastic frontier approach is outlined in the next section.

Conceptual Stochastic Frontier Model

As discussed earlier, in order to measure the efficiency of co-operative firms, a behavioural assumption of cost minimisation is imposed. In this regard, a cost frontier is the appropriate measure for economic efficiency. The general form of a stochastic frontier cost function for panel data may be expressed as (Kumbhakar and Lovell, 2000; Battese and Coelli, 1992):

$$C_{ft} = C(w_{ft}, y_{ft}; \beta) + (v_{ft} + u_{ft}) \quad , f=1, \dots, F, t=1, \dots, T, \quad (1)$$

where C_{ft} is the actual cost of the f -th co-operative in the t -th time period; $C(w_{ft}, y_{ft}; \beta)$ denotes the theoretical cost function; w_{ft} is a $k \times 1$ vector of input prices for the f -th co-operative in the t -th time period; β is a vector of parameters to be estimated; v_{ft} is assumed to be an independently and identically distributed $N(0, \sigma_v^2)$ stochastic error term, and independent of u_{ft} ; u_{ft} is assumed to be an independently and identically distributed non-negative truncation of the $N(0, \sigma_u^2)$ distribution, and thus accounts for cost inefficiency in production. The most common assumptions are the normal distribution for v_{ft} and the exponential, truncated normal (usually the half-normal), or gamma distribution for u_{ft} . The above model accommodates both balanced and unbalanced panel data.

The general procedure for estimating cost efficiency using equation (1) is to first estimate β and $\varepsilon_{ft} = v_{ft} + u_{ft}$ and then to calculate cost efficiency for each observation in the sample as the conditional expectation $E(\exp(-u_{ft}) | \varepsilon_{ft})$. This provides an estimate of cost efficiency as the ratio of frontier (i.e., efficient) cost to actual cost. If distributional assumptions are imposed on the error terms, the approach involves determining the density function of ε_{ft} , $f(\varepsilon_{ft})$, and the joint density function $f(u_{ft}, \varepsilon_{ft})$ and then obtaining an expression for the conditional mean of $\exp(-u_{ft})$ based on the distribution $f(u_{ft} | \varepsilon_{ft})$. Based on the approach proposed by Jondrow et al. (1982) for disentangling the inefficiency effect and assuming a truncated-normal distribution, $u_{ft} \sim N[\mu_f, \sigma_u^2]$, for the inefficiency effect, the firm specific inefficiency term is:

$$E[u_{ft} | \varepsilon_{ft}] = \frac{\sigma \lambda}{1 + \lambda^2} \left[\frac{\phi(\mu_f / \sigma \lambda - \varepsilon_{ft} \lambda / \sigma)}{1 - \Phi(\mu_f / \sigma \lambda - \varepsilon_{ft} \lambda / \sigma)} - (\mu_f / \sigma \lambda - \varepsilon_{ft} \lambda / \sigma) \right] \quad (2)$$

where $\mu_f = \delta'z$, $\sigma = \sqrt{\sigma_v^2 + \sigma_u^2}$, and $\lambda = \sigma_u / \sigma_v$, μ_f is the mode/mean of the truncated normal distribution. The above formulation collapses to the half-normal distribution efficiency estimates (Aigner et al., 1977) if $\mu_f = 0$.

Once point estimates of u_f are obtained based on equation (2), estimates of the cost efficiency (CE_{ft}) of each co-operative in an industry can be obtained from: $CE_{ft} = \exp(-\hat{u}_{ft})^2$, where \hat{u}_{ft} is an estimate of $E(u_{ft} | \varepsilon_{ft})$.

² In a standard stochastic frontier approach, inefficiency is measured relative to the estimated frontier, rather than the best-practice co-operative, that is, relative to zero value for \hat{u}_{ft} which is not achieved by co-operative in the sample.

Econometric Model

Stochastic Frontier

In empirical efficiency studies the most commonly used functional forms are the Translog and Cobb-Douglas forms. The Translog form (Diewert and Wales, 1987) does not impose any technological restriction and allows the economies of scale, size and density to vary with output. Flexible functional forms such as Translog provide a second order approximation to the true underlying (but unknown) technology. For firm $f=1, \dots, F$ at time $t=1, \dots, T$, the stochastic Translog cost function is used in this study:

$$\ln(C_{ft}) = \beta_0 + \sum_i \beta_i \ln w_{ift} + 0.5 * \sum_i \sum_j \beta_{ij} \ln w_{ift} \ln w_{jft} + \sum_i \beta_{iy} \ln w_{ift} \ln y_{ft} + \beta_y \ln y_{ft} + 0.5 \beta_{yy} (\ln y_{ft})^2 + (v_{ft} + u_{ft}) \quad (3)$$

$$u_f = \delta' z_f + \eta_f \quad (4)$$

where C_{ft} is the observed cost for the f -th co-operative firm in the t -th time period, w_{ift} is the price for the i -th input of the f -th co-operative firm in the t -th time period (i.e., labour, capital and materials), y_{ft} is output (i.e., value added) for the f -th co-operative firm in the t -th time period, z_f 's are variables hypothesized to affect efficiency, in this case financial leverage (e.g., liability to total asset ratio) and firm size (e.g., gross sales); the β 's and δ 's are parameters to be estimated, and v and u are defined as before. Equations (3) and (4) are estimated separately in two stages³, where the first step is to estimate a standard stochastic frontier model (equation 3), and the second step is to estimate the relationship between (estimated) u and z (equation 4).

The regularity conditions require that the cost function in equation (3) be linearly homogeneous, non-decreasing and concave in input prices. For the Translog cost function to satisfy the linear homogeneity property of the cost functions, the following parameter restrictions must hold:

$$\sum_{i=1}^n \beta_i = 1, \quad \sum_{j=1}^n \beta_{ij} = 0 \quad \text{and} \quad \sum_{i=1}^n \beta_{iy} = 0.$$

If the cost function is twice differentiable, a combination of Young's theorem and Shepherd's lemma requires that the cross effects in the set of input demand functions be symmetric. However, rather than applying Young's theorem to the actual cost function to obtain a set of restrictions, it can instead be applied to the Translog approximation, so long as the Translog approximation is twice continuously differentiable over the relevant range. This yields the following set of parameter restrictions: $\beta_{ij} = \beta_{ji}$.

Estimation of equations (3) and (4) can be implemented using different stochastic frontier methods: cross-sectional approach, fixed effects and random effects panel data approaches, latent class stochastic frontier approach, and random parameter stochastic frontier approach. The standard modeling approach to econometrically scrutinize the effects of heterogeneity in technology on efficiency across firms is to incorporate a firm specific fixed or random intercept term in the production, cost, or profit function. The fixed effects model is an extension of the basic stochastic frontier model where the constant term is replaced with a complete set of firm dummy variables. One issue is that the estimators of the stochastic frontier model with fixed effects may be persistently biased

³ An alternative approach is to use a one-stage estimation. Wang and Schmidt (2002) argue strongly for one-step estimation whenever one is interested in the effects of firm characteristics on efficiency levels. However, given the complexity of the random parameters model, and a problem with model convergence, the two-stage approach was adopted here.

due to the ‘incidental parameter problem’⁴ when the time span of the panel is small (Greene, 2002c; Greene, 2002). With the fixed effects approach, identification may be difficult, since the number of parameters increases with the number of firms.

The random effects model is obtained by assuming that u_f is time invariant and also uncorrelated with the included variables in the model. However, with the random effects specification, one must impose strong distributional assumptions on both v_{ft} and u_{ft} , as well as the unlikely assumption that the u_{ft} are uncorrelated with the explanatory variables. The Hausman (1978) misspecification test can be used to decide whether to use a fixed-effects model or a random-effects model. However, estimation of the frontier with only fixed or random effects in the intercept terms may result in inefficient estimates of the slope coefficients and invalid inferences of the results (Biorn et al., 2002). In addition, both random and fixed effects cost frontier models assume that any unobserved heterogeneity among co-operatives is completely due to their differences in cost efficiency (Farsi and Filippini, 2003). For example, in the fixed effects model, since the fixed firm-specific effects capture both observed and unobserved time-invariant factors, this may lead to underestimation of cost efficiency.

In previous panel data efficiency studies, heterogeneity in the distribution technology across firms is assumed to impact the density function in the simple form of a random effect model. According to Baltagi (2005) a fixed or random effects specification assume that all slope parameters are the same for all firms, whereas the intercept is firm specific. This is a very restrictive assumption as there is no reason to assume a priori that the intercept is the only firm specific parameter. In practice, firms’ technologies may be heterogeneous rather than homogeneous (Tsionas, 2002; Greene, 2002; Greene, 2002; Orea and Kumbhakar, 2004; Huang, 2004; Battese et al., 2004; Greene, 2002). The underlying belief that all firms share the same technology can be challenged, particularly for samples including a large and heterogeneous set of agribusiness co-operative firms. Agribusiness firms operate under different geographical and agro-ecological conditions and managed by people with different managerial and technical skills. In addition, although co-operatives may have access to the same technology, they differ in the speed with which they adopt technological innovation. The implication is that firms within a sector use different technologies. Models that examine the effect of policy measures (e.g., financial leverage policy) at the co-operative firm level should account for such differences. If the assumption that firms’ technology are homogeneous is not valid, technological differences may be incorrectly labelled as (in)efficiency. Thus, it would be more appropriate to distinguish technological differences and technology-specific inefficiency rather than simply assume that firms share the same technology (Biorn et al., 2002).

One approach to overcome this problem is to use a two-stage analysis where firms are first segregated into several classes and then separate frontiers for each class of firms are estimated (Berger and Mester, 1997). However, one cannot infer that the technologies of firms within the same group will give rise to similar marginal responses. In addition, such an approach has the disadvantage of estimating the frontier of a particular class without using information regarding the other classes. To overcome this problem, the Finite Mixture Model (FMM) approach has been used in different studies. FMM was first proposed by Heckman and Singer (1984) for use in duration models and further extended to stochastic frontier models by Greene (2002).

⁴ According to Neyman and Scott (1948), in panel data with T observations per firm and unobservable firm-specific effects, the maximum likelihood estimators of the common parameters are in general inconsistent since the fixed effect approach introduces many parameters into the model.

In this study, the random parameters model is proposed for use. One of the main advantages of the random parameters model is its ability to control for unobserved technological heterogeneity among co-operatives. In particular, panel data models provide a better opportunity to control for such heterogeneities. Potentially unobserved technological characteristics may affect the production costs but are not necessarily indicative of different efficiencies. The inefficiency measures may therefore be affected by these confounding factors.

The random parameters stochastic frontier model is applied to accommodate unobserved differences in technologies that might be inappropriately labelled as inefficiency. This heterogeneity in technology can be analyzed through specification of a model of random parameters. As Orea and Kumbhakar (2004) point out:

Estimation of [frontier cost] functions rests on the assumption that the underlying production technology is common to all producers. However, firms in a particular industry may use different technologies. In such a case estimating a common frontier function encompassing every sample observation may not be appropriate in the sense that the estimated technology is not likely to represent the 'true' technology. That is, the estimate of the underlying technology may be biased. Furthermore, if the unobserved technological differences are not taken into account during estimation, the effects of these omitted unobserved technological differences might be inappropriately labelled as inefficiency. (pp. 169-170).

The general random parameters stochastic cost frontier formulation (Greene, 2002) is as follows:(Tsionas, 2002; Huang, 2004; Tsionas, 2002)

$$C_{ft} = C(w_{ft}, y_{ft}; \beta_f) + (v_{ft} + u_{ft}), \quad f = 1, \dots, F, \quad t = 1, \dots, T, \quad v_{ft} \sim N[0, \sigma_v^2] \quad (5)$$

Inefficiency Distribution:

$$\begin{aligned} u_{ft} &= |u_{ft}|, \quad u_{ft} \sim N[\mu_f, \sigma_{uf}^2] \\ \mu_f &= \delta_f' z_f \\ \sigma_{uf} &= \sigma_u \exp(\gamma_f' q_f) \end{aligned} \quad (6)$$

Parameter Heterogeneity:

$$\begin{aligned} \beta_f &= \beta + \xi_\beta d_f + \Gamma_\beta v_{\beta_f} \\ \delta_f &= \delta + \xi_\delta d_f + \Gamma_\delta v_{\delta_f} \\ \gamma_f &= \gamma + \xi_\gamma d_f + \Gamma_\gamma v_{\gamma_f} \end{aligned} \quad (7)$$

where C_{ft} , w_{ft} , y_{ft} and β_f are costs of production, input prices, output and the parameter estimates, respectively, for the f -th firm. The parameters β_f are distributed according to a K -variate normal distribution as: $\beta_f \sim N(\bar{\beta}, \Omega)$, $f=1, \dots, F$. where $\bar{\beta}$ is a $k \times 1$ vector of parameter means, Ω is a $K \times K$ positive definite covariance matrix. $\beta_f | \bar{\beta}, \Omega$ are assumed to be independent. The d_f vector includes variables related to the distribution of the random parameters and these are time-invariant; v_{jf} , $j=\beta, \delta, \gamma$ parameterize random variation which is assumed to have mean vector zero and known diagonal covariance matrix Σ_j . $\beta_f(\beta, \xi_\beta, \Gamma_\beta)$, $\delta_f(\delta, \xi_\delta, \Gamma_\delta)$ and $\gamma_f(\gamma, \xi_\gamma, \Gamma_\gamma)$ are matrices of parameters to be estimated; μ_f is the mode/mean of truncated normal distribution; z_f are operating environmental factors affecting the inefficiency effect; q_f is operating environment variables affecting the variance of the inefficiency effects. The parameter σ_v^2 is variance of v_{ft} , and σ_{uf}^2 is variance of u_{ft} .

In order to estimate the parameters of equations (5) to (7), the unobserved random term u_{jf} must be integrated out. Since the integrals will not exist in the closed form, but instead they are in the form of expectations, they can be estimated by simulation. Thus, the simulated log likelihood is defined as:

$$\begin{aligned} \text{LogL}_s &= \sum_{f=1}^N \frac{1}{R} \sum_{r=1}^R \sum_{t=1}^T \ln \frac{1}{\sqrt{2\pi}} + \ln \Phi \left(\frac{\mu_{fr} / (\sigma_{ufr} / \sigma_v) \pm [(C_{ft} - C(w_{fr}, y_{fr})) (\sigma_{ufr} / \sigma_v)]}{\sqrt{(\sigma_{ufr} + \sigma_v)}} \right) \\ &\quad - \ln \Phi \left[\frac{\mu_f}{\sigma_{ufr}} \right] - \ln \sqrt{\sigma_{ufr}^2 + \sigma_v^2} - \frac{1}{2} \left(\frac{\mu_f \pm (C_{ft} - C(w_{fr}, y_{fr}))}{\sqrt{\sigma_{ufr}^2 + \sigma_v^2}} \right)^2 \\ &= \sum_{f=1}^N \frac{1}{R} \sum_{r=1}^R \sum_{t=1}^T \log P_{ftr} \end{aligned} \quad (8)$$

The maximum simulated likelihood estimator is obtained by maximizing (8) over the full set of structural parameters (for more detail on this see Train (2002) and Greene (2002)). Firm specific estimates of the parameters, θ_f [$\beta_f(\beta, \xi_\beta, \Gamma_\beta)$], δ_f ($\delta, \xi_\delta, \Gamma_\delta$) and γ_f ($\gamma, \xi_\gamma, \Gamma_\gamma$) are required in order to estimate cost efficiency. Greene (2002) suggests an estimate of the posterior, conditional mean, for the parameter estimates as follows:

$$\hat{\theta}_f = \frac{\frac{1}{R} \sum_{r=1}^R \theta_{fr} \exp\left(\sum_{t=1}^T \log P_{ftr}\right)}{\frac{1}{R} \sum_{r=1}^R \exp\left(\sum_{t=1}^T \log P_{ftr}\right)} = \frac{\frac{1}{R} \sum_{r=1}^R P_{fr} \theta_{fr}}{\frac{1}{R} \sum_{r=1}^R (P_{fr})} \quad (9)$$

where R is the number of repetitions (i.e., draws of m) on m_{jf} , P_{ftr} is the (probability) contribution of the f -th co-operative at time period t to the likelihood. This can also be computed by simulation during computation of the likelihood function. The firm specific inefficiencies are then based on firm specific expected values of the random parameters.

Data Description

The costs of production, wages and salaries, number of full-time and part-time employees, volume of sales, costs of goods sold, long-term debt, number of members, assets, liabilities and other financial data are obtained from the annual surveys of agribusiness co-operatives conducted by the Canadian Co-operative Secretariat (CCS), Government of Canada. Of approximately 1300 total agriculture-based co-operatives, approximately 900 reported to the Canadian Co-operative Secretariat in 2001. The agricultural marketing and supply co-operatives represent approximately 450-550 reporting co-operatives. Three provinces account for the majority of the fruit production in Canada. Apple production is concentrated mostly in Ontario, BC and Quebec; berry and grape production in BC and Ontario; and tree fruit production in Ontario and BC (Agriculture and Agri-Food Canada, 2003)..

This study focuses on an unbalanced panel of 54 fruit (British Columbia, Ontario and Quebec) and vegetable (Alberta, British Columbia, Saskatchewan, Ontario and Quebec) co-operatives over the period 1984-2001. Data for the GDP deflator, fixed investment deflator, interest rate, raw material price indices and farm input price indices are gathered from Statistics Canada (CANSIM) for the period 1984-2001.

Raw material /Farm Input Prices (M): Raw materials are treated as an aggregate input, excluding capital and labour which are dealt with separately. Raw material price indices are collected from Statistics Canada database, CANSIM. Costs of good sold is used as a proxy for the value of raw materials.

Capital Price (K): According to the opportunity cost principle, the unit cost of capital for a firm should be calculated as the rental value of the capital stock, as if the capital were being rented. The capital input group is an aggregate of land, buildings, machinery and equipment. Using the GDP Deflator and fixed capital price index, the relative price of one unit of capital with respect to production q , is calculated for Canada for each year⁵. In this study, per unit user cost of capital (r_k) is calculated as $r_k = (i - \pi + \delta) * q$, where i is the opportunity cost of capital, δ is the capital depreciation rate, q is the acquisition of capital and π is the rate of inflation in the economy.

Price of Labour (L): The labour input consists of full time and part-time labour. Both the number of employees and the total salary and wages are available from the sample data, but with a high incidence of measurement errors. The per hour wage rate is calculated assuming 40 working hours per week. Where there are outliers, the data are truncated at \$25 per hour from above and \$10 per hour from below based on aggregate wage information from Statistics Canada.

Output (y): The output variable represents value added (sales minus cost of goods sold). One of the challenges in estimating cost frontiers for fruit and vegetable marketing co-operatives is that the direct measure of output, y , is difficult if not impossible to quantify accurately. Thus, value added is used as a proxy for y .

Total Cost (C): The total cost represents the sum of expenses for materials, labour, and capital for the firm. Prior to estimation, value added and all price indexes are normalized to one at the mean of the pooled sample.

Debt to asset ratio (D/A): Debt to asset ratio is used as a measure of the degree of financial leverage.

Volume of Sales: Volume of sales is used as a proxy for co-operative size. Other firm size indicators used in the literature include dollar value of assets and the number of employees. Table 1 provides descriptive statistics for the unbalanced sample observations of fruit and vegetable marketing co-operatives over the period 1984-2001.

Results

Model selection tests are conducted to choose from among competing stochastic frontier models (i.e., the random effects model and the random parameters model) (Table 2). Results suggest that the random parameters model outperforms the random effects stochastic frontier models. Consistent with the theoretical argument, the degree of efficiency is found to be higher for the random parameters approach (i.e., 0.72 percent efficient) than that from the random effects (i.e., 12 percent efficient) approach. The main conclusion of this study is that the degree of efficiency is greater when taking into account unobserved heterogeneity in technology than it would be suggested by the conventional measure. These results suggest that, from a theoretical perspective, the choice of model may matter in the estimation of efficiency and its policy implication. Ignoring the reality that different co-operatives face different technologies may be misleading so far as efficiency is concerned.

Since there are two major types of products that are handled by the fruit and vegetable co-operatives (and the data for these attributes are also available), two separate random parameters models are estimated and tested: one with (i.e., $\beta_{fi} = \beta + \xi_{\beta} \text{fruit}_f + \Gamma_{\beta} m_{\beta_f}$, $\text{fruit} = 1$, for fruit co-operatives;

⁵ Boadway (1985), proposed the following formula to calculate the service cost of capital:

$$r_k = q \left(\frac{i + \delta - r_q - \pi}{1 - \pi} \right) (1 - \phi) \left(1 - \frac{\tau \alpha}{i + \alpha} \right). \text{ where } i \text{ is the opportunity cost of capital, } \delta \text{ is the capital depreciation rate, } r_q$$

is the rate of growth in the acquisition of capital q , π is the rate of inflation in the economy, τ is the corporate income tax rate, ϕ is the investment tax credit, and α is the percentage capital cost allowance (CCA) rate (percent).

fruit=0, for vegetable co-operative) and one without (i.e., $\beta_{fi} = \beta + \Gamma_{\beta} m_{\beta_r}$) heterogeneity in means of the random parameters. A Likelihood ratio test is conducted to select the best model. At a 10 percent significance level, the random parameters stochastic frontier model without heterogeneous means is rejected in favour of the random parameters stochastic frontier model with heterogeneity in the means. Thus, the following results for fruit and vegetable co-operatives are based on the estimates for the random parameters model with heterogeneous means.

A single cost frontier is estimated for both fruit and vegetable co-operatives. The simulated maximum likelihood parameter estimates for the fruit and vegetable co-operatives cost frontier are provided in Table 3. Before estimating the cost efficiency scores, the regularity conditions of cost function are checked. Linear homogeneity and symmetry in input prices are imposed prior to estimation. Monotonicity and concavity are checked and both are satisfied at the mean values.

Before turning to an investigation of cost efficiency, the estimated cost structure of the estimated frontier is explored. Table 4 reports input substitution elasticities and input price elasticities. For fruit and vegetable co-operatives, the own-price elasticity of labour is larger than that for capital and raw material; all three inputs are substitutes for each other.

Table 5 shows the estimated returns to scale. Based on the mean value of the returns to scale it can be seen that both fruit and vegetable co-operatives are operating in the region of increasing returns to scale. This may suggest that larger-sized co-operatives are more cost effective.

In the estimation of a stochastic frontier the variance parameters have important implications. Given the estimates of σ_u and σ_v , the results suggest that 81 percent of the deviation from the frontier cost of production is attributable to cost inefficiency. In addition, the fact that λ is statistically significant suggests the existence of cost inefficiency for the sample co-operatives. Table 6 reports the average cost efficiency for the fruit and vegetable co-operatives. The estimated mean cost efficiency is 0.72 or 72 percent (Table 6).

Table 7 presents the relationship between average sample observations characteristics and efficiency for fruit and vegetable marketing co-operatives. For fruit and vegetable co-operatives, sample observations with large sales values are characterized by lower efficiency. However, there is no definite relationship between asset values and efficiency for fruit and vegetable co-operative sample observations. As well, the relationship between leverage and efficiency is ambiguous. In general, observations with higher return on assets appear to be more efficient as compared to those with lower returns. Sample observations with larger numbers of employees are more efficient.

Table 8 presents descriptive statistics for individual co-operative. For 20 (80) percent of fruit and vegetable co-operatives, individual firm efficiency and firm size are positively (negatively) correlated over the sample period. This indicates that the efficiency of 20 percent of fruit and vegetable co-operatives increases with firm size whereas the efficiency of 80 percent of fruit and vegetable co-operatives decreases with firm size. For 39 percent of fruit and vegetable co-operatives, efficiency and financial leverage are positively correlated, suggesting that their efficiency increases with the financial leverage. On the other hand, for 61 percent of fruit and vegetable co-operatives, efficiency and financial leverage are negatively correlated, suggesting that firm efficiency decreases with the financial leverage. For fruit and vegetable co-operatives, a summary of the firms' average, minimum and maximum efficiencies the same period is provided in Table 8. Firms' average efficiency ranges between 0.615 and 0.772 while firms' minimum and maximum efficiency ranges, respectively, between 0.032 and 0.680, and 0.756 and 0.959. The correlation between firms' average efficiency and firm size is 0.023 while the correlation between the firms' average efficiency and leverage ratio is -0.02.

The random parameters Tobit regression is used to rigorously (i.e., statistically) investigate the relationship between efficiency and the degree of financial leverage. The Tobit regression random parameter estimates for factors affecting cost efficiency are given in Table 9. The results indicate that co-operative size is quadratically related to cost efficiency. This suggests that smaller-sized and larger-sized fruit and vegetable co-operatives are more cost efficient than medium-sized co-operatives. As discussed earlier, the basic implication of technological and organizational theories emphasizing transaction and agency costs of firm size is that within a specific industry (common production technology) and within a common institutional environment, firm size and efficiency may be linked through a trade-off of economies of scale and transactions costs and agency costs. In the case of fruit and vegetable co-operatives case, transaction and agency costs of size may more than offset the benefits from economies of scale for medium-sized co-operatives as compared to their smaller and larger counterparts. This is particularly possible if the organization cost curve is concave from above and if at the same time the vertical distance between the average costs of production and organizing costs is at its maximum at a medium firm size. The degree of financial leverage is found to have, on average, a negative impact on the cost efficiency of fruit and vegetable co-operatives which may suggest the likely negative impact of financial pressure on co-operative performance. This is consistent with the descriptive results presented in Table 7 and 8.

Previous studies also reported the existence of relationship between the degree of financial leverage and efficiency. These studies revealed that firms may be operating at various levels of cost inefficiency due to differences in their capital structures (Nasr et al., 1998; Rajan and Zingales, 1995; Johnson, 1997; Michaelas et al., 1999). Yet, Nasr et al. (1998) found a positive relationship between efficiency and financial structure, where the linkage is reflective of the motivation provided by Jensen's (1986) free cash flow concept and the credit evaluation concept. Results in this study support Jensen and Meckling's (1976) agency cost concept. Monitoring, bonding, and adverse incentive costs may be incurred in a borrower-lender relationship in order to resolve problems of asymmetric information and misaligned incentives between the two parties (Jensen and Meckling, 1986). From the above, a substantial number of fruit and vegetable marketing co-operatives could be more efficient by adjusting their capital structure.

Concluding Remarks

Evidence from this study suggests that there may be some potential for cost reduction through improved efficiency that would in turn add value to co-operative members' outputs. For example, costs of adding value would have been decreased on average by approximately 28 percent had the co-operatives operated at their respective frontiers. Thus, decision makers of co-operative may focus on using inputs of production (i.e., labour, capital and material) more efficiently in addition to only focusing on increasing their size.

Given the empirical evidence in this study, the following conclusions may be made: i) the approach used to estimate efficiency matters; ii) the estimated cost inefficiencies are statistically significant; iii) there is significant inter-firm variation in efficiency; iv) smaller-sized and larger-sized fruit and vegetable marketing co-operatives are more cost efficient; and v) higher financial leverage has likely contributed to some of the cost inefficiencies.

A few comments on this research are important. The results show that agricultural policy that focuses on improving efficiency of agribusiness firms may have different impacts on different co-operatives. Random parameters stochastic frontier estimation offers a way to model firm-specific behaviour and account for technological heterogeneity across firms. One explanation for the inverse relationship between cost efficiency and financial leverage may be that sticking to co-operative principles might have made it difficult for co-operatives to lower financing costs by raising relatively

cheaper funds from public investors/ stock market. Obtaining sufficient equity capital is expected to improve co-operative efficiency.

There are several ways in which the current research on Canadian agricultural supply and marketing co-operatives may be extended. For example, are there differences in efficiency between traditional co-operative and new generation co-operative structures within the same industry? Are there differences in efficiency between co-operatives and investor-owned firms in the same industry? Does ownership structure matter? Does the geographical location of the firm matter?

References

- Agriculture and Agri-Food Canada. 2003. Canada's Agriculture, Food and Beverage Industry. Web page, [accessed 18 July 2005]. Available at http://atn-riae.agr.ca/supply/3304_e.htm
- Aigner, D. J, C.A.K. Lovell, and P. Schmidt. 1977. Formulation and Estimation of Stochastic Frontier Production Function Models. *Journal of Econometric* 6: 21-37.
- Akridge, J. T., and T. W. Hertel. 1992. Co-operative and Investor-Oriented Firm Efficiency: A Multiproduct Analysis. *Journal of Agricultural Cooperation* 7:1-14.
- Ariyantne, C. B., A. Featherstone, M. R. Langemeier, and D. G. Barton. 1997. An Analysis of Efficiency of Midwestern Agricultural Co-operatives. *Annual Meeting Selected Papers from Western Agricultural Economics Association*, Selected Papers of the 1997 Annual Meeting, July 13-16, 1997, Reno/Sparks, Nevada.
- Ariyaratne, C. B., A. M. Featherstone, M. R. Langemeier, and D. G. Barton. 2000. Measuring X-Efficiency and Scale Efficiency for a Sample of Agricultural Co-operatives. *Agricultural and Resource Economics Review* 29(2):198-207.
- Baltagi, B.H. 2005. *Econometric Analysis of Panel Data*. 3rd ed. New York: Wiley.
- Battese, G. E., and G. S. Corra. 1977. Estimation of a Production Frontier Model: With Application to the Pastoral Zone of Eastern Australia. *Australian Journal of Agricultural Economics* 21(3): 169-79.
- Battese, G., and T. Coelli. 1992. Frontier Production Functions, Technical Efficiency and Panel Data: with Application to Paddy Farmers in India. *Journal of Productivity Analysis* 3:153-69.
- Bauer, P. W. 1990. Recent Developments in the Econometric Estimation of Frontier. *Journal of Econometrics* 46:39-56.
- Berger, A. N. 1993. Distribution-Free Estimates of Efficiency in the U.S. Banking Industry and Tests of the Standard Distributional Assumptions. *Journal of Productivity Analysis* 4:261-92.
- Berger, A. N., and L. J. Mester. 1997. Inside the Black Box: What Explains Differences in the Efficiencies of Financial Institutions? *Journal of Banking and Finance* 21(7): 895-947.
- Berry, D. M. 1994. Private Ownership Form and Productive Efficiency: Electric Co-operatives versus Investor-Owned Utilities. *Journal of Regulatory Economics* 4(6):399-420.
- Biorn, E., K-G. Lindquist, and T. Skjerpen . 2002. Heterogeneity in Returns to Scale: A Random Coefficient Analysis with Unbalanced Panel Data. *Journal of Productivity Analysis* 18(1): 39-57.
- Biorn, E., K-G. Lindquist, and T. Skjerpen . 2002. Heterogeneity in Returns to Scale: A Random Coefficient Analysis with Unbalanced Panel Data. *Journal of Productivity Analysis*, 39-57:18.
- Boadway, R. W. 1985. *The Theory and Measurement of Effective Tax Rates. The Impact of Taxation on Business Activity*. Kingston, Ontario: Queen's University.
- Brown, R., R. Brown, and I. O'Connor. 1999. Efficiency, Bond of Association and Exit Patterns in Credit Unions: Australian Evidence. *Annals of Public and Co-operative Economics* 70(1): 5-23.
- Canadian Co-operative Secretariat. 2004. Co-operatives in Canada (2002 Data). Web page, [accessed 20 July 2005]. Available at http://www.agr.gc.ca/policy/coop/pdf/coop02_e.pdf
- Caputo, M. R., and L. Lynch. 1993. A Nonparametric Efficiency Analysis of California Cotton Ginning Co-operatives. *Journal of Agricultural and Resource Economics*, 18(2): 251-65.

- Charnes, A., W.W. Cooper, and E. Rhodes. 1978. Measuring the Efficiency of Decision Making Units. *European Journal of Operations Research* 2: 429-44.
- Debreu, G. 1951. The Coefficient of Resource Utilization. *Econometrica* 19(3): 273-92.
- Defourny, Jacques, C. A. K. Lovell, and A. G. M. N'gbo. 1992. Variation in Productive Efficiency in French Workers' Co-operatives. *Journal of Productivity Analysis* 3(1-2): 103-17.
- Diewert, W. E., and T. J. Wales. 1987. Flexible Functional Forms and Global Curvature Conditions. *Econometrica* 55:43-68.
- Doyon, M. 2001. A Case Study on Structural Change in the Canadian Dairy Processing Industry and Implications for Dairy Co-operatives. University of Alberta, Edmonton. Web page, [accessed 30 March 2005]. Available at http://www.coop.re.ualberta.ca/symposium_2001/Maurice_Doyon/texte3.htm.
- Esho, N. 2001. The Determinants of Cost Efficiency in Co-operative Financial Institutions: Australian Evidence. *Journal of Banking and Finance* 25(5): 941-64.
- Evans, L. and G. Guthrie. 2002. "A Dynamic Theory of Co-operatives: The Link between Efficiency and Valuation." Web page, [accessed 15 September 2004]. Available at <http://203.96.60.248/vuw/fca/sef/files/Mutuals.pdf>.
- Färe, R., S. Grosskopf, and C. A. K. Lovell. 1985. The measurement of Efficiency of Production. Boston: Kluwer Academic Publishers.
- Farrell, M. J. 1957. The Measurement of Productive Efficiency. *Journal of the Royal Statistical Society Series A* 120(3): 253-90.
- Farsi, M. and M. Filippini. 2003. "Regulation and Measuring Cost Efficiency with Panel Data Models: Application to Electricity Distribution Utilities." Web page, [accessed 17 November 2004]. Available at http://www.ksg.harvard.edu/hepg/Papers/CEPE_WP19.regulation.measure.cost.eff_1-03.pdf.
- Ferrier, G. D., and P. K. Porter. 1991. The Productive Efficiency of U.S. Milk Processing Co-operatives. *Journal of Agricultural Economics* 42:161-73.
- Forsund, F. R., C. A. K. Lovell, and P. Schmidt. 1980. A Survey of Frontier Production Functions and of Their Relationship to Efficiency Measurement. *Journal of Econometrics* 13:5-25.
- French, B. C. 1977. The Analysis of Productive Efficiency in Agricultural Marketing: Models, Methods and Progress, *Traditional View of Agricultural Economics, 1940 to 1970s. A Survey of Agricultural Economics, The American Agricultural Economics Association*. 93-206. Vol. Volume I. Minneapolis: University of Minnesota Press.
- Fukuyama, H., R. Guerra, and W. L. Weber. 1999. Efficiency and Ownership: Evidence from Japanese Credit Co-operatives. *Journal of Economics and Business* 51(6): 473-87.
- Gorton, G., and F. Schmid. 1999. Corporate Governance, Ownership Dispersion and Efficiency: Empirical Evidence from Austrian Co-operative Banking. *Journal of Corporate Finance: Contracting, Governance and Organization* 5(2): 119-40.
- Greene, W. 2002. *Econometric Modeling Guide: LIMDEP: Version 8.0*. Castle Hill: Econometric Software, Inc.
- Greene, W. 2002. Alternative Panel Data Estimators for Stochastic Frontier Models. *Current Developments in Productivity and Efficiency Measurements*, New York University, Department of Economics.

- Greene, W. 2002. Fixed and Random Effects in Stochastic Frontier Models. Working Paper, Web page, [accessed 15 September 2004]. Available at <http://pages.stern.nyu.edu/~wgreene/fixedandrandomeffects.pdf>.
- Hausman, J. A. 1978. Specification Tests in Econometrics. *Econometrica* 46:1251-71.
- Heckman, J., and B. Singer. 1984. A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data. *Econometrica* 52:271-320.
- Huang, H-C. 2004. Estimation of Technical Inefficiencies with Heterogeneous Technologies. *Journal of Productivity Analysis* 21:277-296.
- Jensen, M. C. 1986. Agency Costs of Free Cash Flow, Corporate Finance, and Takeovers. *The American Economic Review* 76(2): 323-29.
- Jensen, M. C., and W. H. Meckling. 1976. Theory of the Firm: Managerial Behavior, Agency Costs, and Ownership Structure. *Journal of Financial Economics* 3(4):305-60.
- Johnson, S. 1997. An Empirical Analysis of the Determinants of Corporate Debt Ownership Structure. *Journal of Financial and Quantitative Analysis* 32(1):47-69.
- Jondrow, J., C. A. Knox Lovell, I. S. Materov, and P. Schmidt. 1982. On Estimation of Technical Inefficiency in the Stochastic Frontier Production Function Model. *Journal of Econometrics* 19:233-238.
- Koopmans, T. C. 1951. *An Analysis of Production as an Efficient Combination of Activities*. in *Activity Analysis of Production and Allocation*, Cowles Commission for Research in Economics, Monograph No. 13, edited by, John Wiley and Sons, New York..
- Kumbhakar, S., and C. A. Knox Lovell. 2000. *Stochastic Frontier Analysis*. Cambridge: New York: Cambridge University Press.
- Lang, G., and P. Welzel. 1999. Mergers among German Co-operative Banks: A Panel-Based Stochastic Frontier Analysis. *Small Business Economics* 13(4): 273-86.
- Lavado, R. 2004. "Benchmarking the Efficiency of Philippine Electric Co-operatives Using Stochastic Frontier Analysis and Data Envelopment Analysis." Web page, [accessed 15 September 2004]. Available at <http://www.uq.edu.au/economics/appc2004/Papers/cs5C2.pdf>.
- Meeusen, W., and J. I. van den Broeck. 1977. Efficiency Estimation from Cobb-Douglas Production Functions with composed error. *International Econometric Reviews* 18: 435-44.
- Michaelas, N., F. Chittenden, and P. Poutziouris. 1999. Financial Policy and Capital Structure Choice in U.K. SMEs: Empirical Evidence from Company Panel Data. *Small Business Economics* 12:113-30.
- Myers, S. C. 1977. Determinants of Corporate Borrowing. *Journal of Financial Economics* 4:147-75.
- Nasr, R. E., P. J. Barry, and P. N. Ellinger. 1998. Financial Structure and Efficiency of Grain Farms. *Agricultural Finance Review* 58(3):33-48.
- Nasr, R. E., P. J. Barry, and P. N. Ellinger. 1998. Financial Structure and Efficiency of Grain Farms. *Agricultural Finance Review* 58(3):33-48.
- Neyman, J., and E. L. Scott. 1948. Consistent Estimation from Partially Consistent Observations. *Econometrica* 16:1-32.
- Orea, L. and S.C. Kumbhakar. 2003. "Efficiency Measurement Using A Latent Class Stochastic Frontier Model ." Web page, [accessed 14 January 2005]. Available at

http://www.celpe.unisa.it/DP/ee_0251.pdf.

- Rajan, R., and L. Zingales. 1995. What Do We Know about Capital Structure? Some Evidence from International Data. *Journal of Finance* 50:1421-60.
- Rajan, R., and L. Zingales. 1995. What Do We Know about Capital Structure? Some Evidence from International Data. *Journal of Finance* 50:1421-60.
- Seiford, L. M., and R. M. Thrall. 1990. Recent Development in DEA: The Mathematical Programming Approach to Frontier Analysis. *Journal of Econometrics* 46(October/November):7-38.
- Sexton, Richard J., and J. Iskow. 1993. What Do We Know About the Economic Efficiency of Co-operatives: An Evaluative Survey? *Journal of Agricultural Cooperation* 8: 15-27.
- Shephard, R. W. 1953. Cost and Production Functions. Princeton: Princeton University Press.
- Singh, S., T. Coelli, and E. Fleming. 2001. Performance of Dairy Plants in the Co-operative and Private Sectors in India. *Annals of Public and Co-operative Economics* 72(4): 453-79.
- Solow, R. M. 1957. Technical Change and the Aggregate Production Function. *Review of Economics and Statistics* 39(3): 312-20.
- Stutzman, J. R., and S. R. Stansell. 1992. An Examination of the Relative Economic Efficiency of Commercial vs. Co-operative Telephone Companies. *Journal of Economics and Finance* 16(2): 47-68.
- Thraen, C. S., D. E. Hahn, and J. B. Roof. 1987. Processing Costs, Labor Efficiency, and Economies of Size in Co-operatively Owned Fluid Milk Plants. *Journal of Agricultural Cooperation* 2: 40-56.
- Train, K. 2002. Discrete Choice: Methods with Simulation. Cambridge: Cambridge University Press.
- Tsionas, M. 2002. Stochastic Frontier Models with Random Coefficients. *Journal of Applied Econometrics* 17: 127-47.
- Tulkens, H. 1993. On FDH Efficiency Analysis: Some Methodological Issues and Applications to Retail Banking Courts and Urban Transit. *Journal of Productivity Analysis* 4:183-210.
- Wang, H-J., and P. Schmidt. 2002. One-Step and Two-Step Estimation of the Effects of Exogenous Variables on Technical Efficiency Levels. *Journal of Productivity Analysis*, 18:129-44.
- Worthington, A. C. 1998. Testing the Association between Production and Financial Performance: Evidence from a Not-for-Profit, Co-operative Setting. *Annals of Public and Co-operative Economics* 69(1): 67-83.
- Worthington, A. C. 1999. Measuring Technical Efficiency in Australian Credit Unions. *Manchester School* 67(2): 231-48.
- Zou, L. 1992. Ownership Structure and Efficiency: An Incentive Mechanism Approach. *Journal of Comparative Economics* 16(3): 399-431.

Figure 1. Estimates of Trends in Market Shares (percent) of Fruit and Vegetable Marketing Co-operatives in Canada (1985-2002)

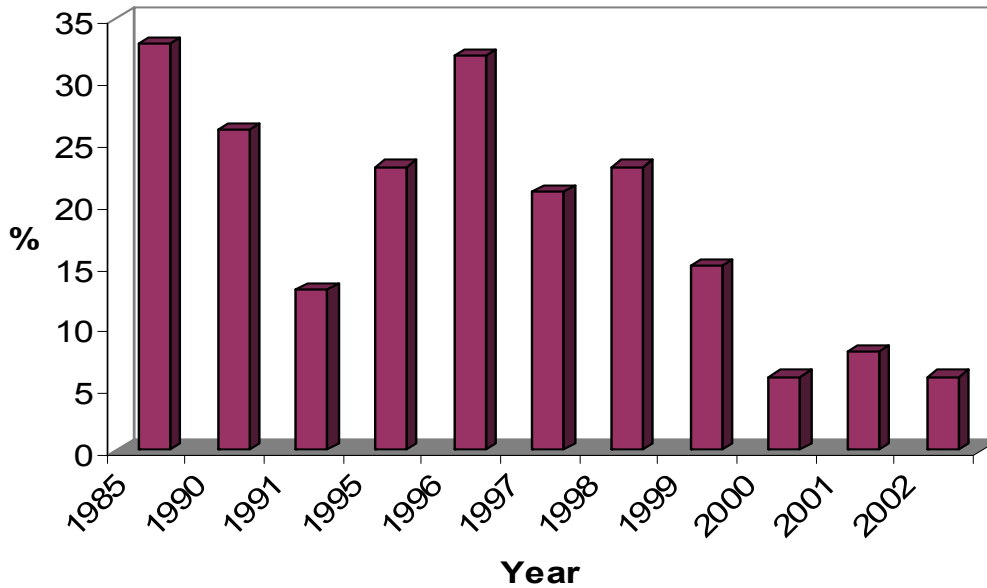


Table 1: Descriptive Statistics (Average and Standard Deviations) for Fruit and Vegetable Marketing Co-operatives by Activity (1984-2001)

	Fruit	Vegetable
Total Costs (Million CAN\$)	5.783 (7.248)	7.174 (8.823)
Sales (Million CAN\$)	7.975 (10.301)	8.71 (11.463)
Value added (million CAN\$)	3.6 (6.237)	2.621 (4.636)
Return on Assets	0.075 (0.188)	0.034 (0.148)
Debt to Assets ratio	0.6085 (0.279)	0.6909 (0.247)
Total Assets (Million CAN\$)	3.884 (5.807)	3.057 (4.505)
Employees (#)	24 (52)	24 (41)
Members (#)	117 (122)	95 (177)
Number of Observation	(n= 213)	(n= 250)

Note: Figures in parentheses are standard deviations

Table 2. Tests Results for Model Selection between Homogeneous Technology and Heterogeneous Technologies Stochastic Frontier Models and the Associated Mean Efficiency Scores

	Homogeneous technology (Random Effects)	Heterogeneous Technologies (Random Parameters without heterogeneity)
LLF	-416.199	-356.495
AIC	858.397	758.990
BIC	912.187	854.158
Mean Cost Efficiency	0.116	0.738
SE of Cost Efficiency	0.200	0.097

Table 3. Parameter Estimates for Random Parameter Stochastic Cost Frontier Model for Fruit and Vegetable Marketing Co-operatives in Canada, 1984-2001

	Posterior Means for Random parameters (β 's)	Posterior Heterogeneity in the means (Fruit Dummy) – (ξ 's)	Posterior Standard Deviation of Random Parameters (Γ_{β} 's)
Constant	14.568*** (0.078)	-0.307*** (0.078)	1.121*** (0.020)
Raw	0.351 (0.340)	-1.745*** (0.411)	0.519*** (0.082)
Labour	0.432*** (0.121)	-0.281** (0.142)	0.160*** (0.028)
Value Added	0.555*** (0.037)	-0.345*** (0.044)	0.269*** (0.006)
Raw ²	-0.409 (1.674)	-5.817*** (2.240)	0.711 (0.704)
Raw*Labour	-0.045 (0.485)	0.229 (0.664)	1.209*** (0.227)
Labour ²	-1.733*** (0.522)	2.832*** (0.639)	1.373*** (0.142)
Raw*Value	0.062 (0.113)	-0.203 (0.140)	0.033 (0.029)
Labour*Value	0.188*** (0.055)	-0.160*** (0.064)	0.149*** (0.011)
Value ²	0.036*** (0.014)	-0.021 (0.017)	0.109*** (0.003)
Time	0.024*** (0.003)	-- --	-- --
σ_u	0.460		
σ_v	0.223		
σ	0.511*** (0.008)		
λ	2.061*** (0.100)		
LLF	-347.720		
Firms	54		
N	463		
Halton draws	200		

Note: *, **, *** refers to 10 percent, 5 percent and 1 percent, respectively, level of significance. Figures in parentheses are standard deviations

Table 4. Input Elasticities of Substitution and Input Price Elasticities for Fruit and Vegetable Co-operatives

	Input Substitution Elasticities			Input Demand Price Elasticities		
	Material	Labour	Capital	Material	Labour	Capital
Material	-0.993	0.658	10.692	-0.763	0.506	8.219
Labour	0.658	-64.566	172.255	0.112	-10.184	0.894
Capital	10.692	172.255	-616.625	0.651	12.387	-0.093

Table 5. Average Returns to Scale for Fruit and Vegetable Co-operatives in Canada, 1984- 2001

Variable	Mean	Std. Dev.
Fruit	3.249	0.971
Vegetable	3.284	0.782
Overall	3.268	0.873

Table 6. Distribution of Cost Efficiency for Fruit and vegetable Co-operatives in Canada, 1984-2001

Variable	Mean	Std. Dev.	Minimum	Maximum	CV
Fruit	0.720	0.116	0.257	0.918	0.161
Vegetable	0.720	0.117	0.032	0.959	0.163
Overall	0.720	0.117	0.032	0.959	0.163

Table 7. Average Fruit and Vegetable Co-operative Firm Characteristics by Efficiency Indices Categories, 1984-2001

Firm Characteristics	Efficiency Scores						Mean
	< 0.50	0.5 - 0.59	0.60 - 0.69	0.70 - 0.79	0.80 - 0.89	> 0.89	
Cost ^(a)	9.825	8.868	8.104	5.961	4.769	2.182	6.534
Sales ^(a)	10.571	10.357	9.621	7.880	7.130	4.492	8.372
Value Added ^(a)	1.403	3.025	2.910	3.186	3.379	3.718	3.071
Assets ^(a)	2.243	3.727	3.722	3.570	2.916	5.110	3.437
ROA ^(b)	0.049	0.027	0.033	0.057	0.071	0.092	0.052
Leverage ^(b)	0.637	0.713	0.682	0.641	0.629	0.656	0.653
Employee ^(c)	10	18	22	27	25	35	24
Member ^(c)	82	116	131	102	86	106	105
N	24	35	104	192	99	9	463

Note: (a) million Canadian dollars; (b) = ratio; (c) = number; ROA= return on assets; leverage= liability to asset ratio; and N = number of observations in a panel.

Table 8. A Summary of Average Efficiency, Sales, Assets and Debt to Asset Ratio for Individual Fruit and Vegetable Co-operative Firms over the Period 1984-2001

Fruit Firm	Efficiency			Sales (million \$)			Assets (Million \$)			Debt to Asset ratio		
	Average	Minimum	Maximum	Average	Minimum	Maximum	Average	Minimum	Maximum	Average	Minimum	Maximum
2	0.710	0.353	0.898	10.295	5.306	18.948	1.913	1.040	3.471	0.374	0.161	0.663
4	0.753	0.600	0.837	2.707	1.760	4.395	0.611	0.258	1.026	0.757	0.317	1.000
5	0.725	0.521	0.925	37.587	12.804	48.711	24.083	16.326	29.401	0.655	0.506	0.829
6	0.695	0.422	0.906	7.752	4.363	16.188	3.836	2.975	5.181	0.953	0.706	0.990
8	0.752	0.605	0.857	15.138	13.073	17.417	8.307	5.645	12.846	0.846	0.673	0.960
11	0.707	0.481	0.838	52.494	48.593	59.283	11.077	8.918	12.299	0.759	0.650	0.941
13	0.719	0.577	0.914	14.839	11.526	18.272	9.531	6.888	11.197	0.610	0.318	0.871
17	0.736	0.507	0.847	9.030	5.994	17.318	3.816	2.672	5.012	0.914	0.863	0.981
18	0.697	0.486	0.867	17.298	12.771	22.383	2.710	2.408	3.023	0.884	0.728	1.000
19	0.713	0.448	0.864	13.427	5.016	23.577	4.223	1.724	7.318	0.781	0.467	0.942
21	0.737	0.441	0.845	9.132	3.115	22.271	2.026	1.022	2.990	0.636	0.295	0.965
22	0.678	0.473	0.842	13.152	7.573	21.347	1.997	1.150	3.277	0.767	0.719	0.811
24	0.737	0.032	0.892	0.206	0.031	1.721	0.057	0.037	0.118	0.125	0.020	0.519
25	0.632	0.319	0.959	3.380	0.631	4.350	0.360	0.198	0.718	0.849	0.749	1.000
28	0.738	0.645	0.799	1.180	1.044	1.387	1.665	1.612	1.780	0.610	0.590	0.637
53	0.734	0.358	0.824	8.746	2.772	23.765	0.971	0.116	3.732	0.591	0.459	0.798
55	0.734	0.606	0.864	2.601	1.820	3.748	1.186	0.548	2.230	0.695	0.578	0.785
63	0.615	0.417	0.842	1.254	0.248	1.780	0.120	0.073	0.176	0.724	0.452	0.873
64	0.728	0.638	0.756	0.054	0.053	0.060	0.212	0.160	0.420	0.507	0.442	0.767
167	0.721	0.600	0.794	0.112	0.036	0.213	0.254	0.215	0.302	0.997	0.990	1.000
223	0.735	0.513	0.900	0.531	0.296	0.787	0.168	0.129	0.255	0.782	0.279	1.000
229	0.692	0.433	0.911	0.862	0.104	1.910	0.354	0.127	0.715	0.543	0.215	0.747
233	0.744	0.621	0.860	11.299	7.694	16.726	8.655	6.434	11.228	0.902	0.864	0.933
235	0.720	0.500	0.885	15.223	4.353	27.598	3.689	1.082	6.640	0.558	0.339	0.713
244	0.751	0.678	0.839	11.028	5.688	15.214	4.565	2.413	7.790	0.419	0.177	0.674
248	0.715	0.624	0.849	3.752	3.046	4.361	1.601	1.257	1.845	0.375	0.282	0.445

Table 8 continued

250	0.740	0.604	0.823	1.423	1.140	1.705	1.105	0.660	1.538	0.862	0.789	0.916
254	0.748	0.475	0.908	9.167	5.661	13.998	5.994	3.298	12.648	0.916	0.828	1.000
265	0.734	0.680	0.826	5.843	4.128	6.451	0.782	0.678	0.939	0.773	0.726	0.844
266	0.724	0.606	0.809	0.515	0.333	0.780	0.246	0.169	0.332	0.913	0.888	0.941
277	0.772	0.666	0.837	0.177	0.143	0.190	0.278	0.254	0.345	0.472	0.412	0.575
279	0.732	0.639	0.860	0.502	0.319	0.711	0.341	0.277	0.417	0.257	0.161	0.440
284	0.735	0.592	0.812	1.245	0.994	1.443	2.191	1.837	3.140	0.648	0.540	0.829
351	0.642	0.257	0.918	0.282	0.056	0.603	0.171	0.013	0.471	0.207	0.000	0.387
352	0.701	0.484	0.894	0.325	0.117	0.778	0.346	0.121	0.527	0.585	0.137	0.832
353	0.720	0.469	0.861	0.075	0.018	0.206	0.074	0.013	0.120	0.065	0.000	0.354
354	0.736	0.586	0.821	0.571	0.336	1.226	0.370	0.224	0.679	0.258	0.052	0.393
355	0.723	0.412	0.866	0.531	0.201	0.857	0.397	0.137	0.671	0.386	0.007	0.680
359	0.668	0.356	0.869	0.814	0.129	4.672	0.204	0.049	0.451	0.681	0.315	0.962
360	0.698	0.502	0.909	0.572	0.305	0.921	0.347	0.205	0.603	0.549	0.275	0.848
363	0.711	0.489	0.928	3.343	0.415	6.511	1.048	0.385	2.111	0.856	0.473	0.932
364	0.741	0.671	0.874	1.260	0.889	1.679	0.660	0.514	0.740	0.939	0.886	1.000
365	0.721	0.596	0.800	1.560	1.176	1.934	0.816	0.610	1.213	0.811	0.577	1.000
367	0.707	0.545	0.846	1.666	1.149	2.222	1.105	0.951	1.369	0.711	0.664	0.789
380	0.731	0.631	0.856	1.411	1.068	1.671	0.881	0.642	1.120	0.231	0.140	0.334

Table 9. Random Parameter Tobit Regression Parameters Estimates for the Determinants of Cost Efficiency for Fruit and Vegetable Co-operatives in Canada, 1984-2001

Variables	Parameters		
Mean Constant	δ_0	0.749***	(0.010)
Std. of Constant	Γ_{δ_0}	0.001	(0.004)
Mean Sales	δ_S	-0.188***	(0.049)
Std. of Sales	Γ_{δ_S}	0.001	(0.015)
Mean Sales ²	δ_{SS}	0.145***	(0.056)
Std. of Sales ²	$\Gamma_{\delta_{SS}}$	0.001	(0.020)
Mean Debt/Asset ratio	δ_{DA}	-0.014	(0.014)
Std. of Debt/Asset ratio	$\Gamma_{\delta_{DA}}$	0.023***	(0.005)
σ		0.114***	(0.002)
LLF		342.876	
Chi squared		685.752	
Firms		54	
Firms x Time		463	
Halton		100	
Note: *, **, *** refers to 10 percent, 5 percent and 1 percent, respectively, level of significance.			
Figures in parentheses are standard deviations			