Efficiency and Economic Performance: An Application of the MIMIC Model

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Using measures of allocative, technical, and overall efficiency as indicators of a latent "performance" variable, and a set of farm operating ratios as indicators of the amount of effort to improve the quality of feeding, breeding, and labor productivity, we employ a multiple-indicator, multiple-cause (MIMIC) model of Alberta dairy production to determine the factors that contribute to economic performance. Gains in performance may be made through increased milk yield, herd size, breeding-program quality, and labor quality, but not by operator experience or increased expenditures on feeding programs. Consequently, the industry trend toward larger dairy herds may indeed improve the economic performance of dairy operators.

Key words: Alberta, dairy, efficiency, MIMIC model, production frontier

Introduction

Although Canada's system of dairy supply management continues to be protected from world competition by a regime of tariffs, producers acknowledge the inevitability of a move toward free trade in milk and dairy products. In anticipation of such open competition, dairy farmers are beginning to overhaul their operations in hopes of not only retaining the domestic market, but developing export markets as well. The most common and widely reported strategy has been herd expansion (*Western Producer*). However, it is not universally agreed that there are significant economies of scale in Canadian dairy (Romain and Lambert 1994b); thus, many feel that the most significant improvements may be found in new feeding strategies and breeding programs (Kennelly). Because of this uncertainty and the significant financial commitment that each entails, it is essential that dairy producers, their feed, genetics, and equipment suppliers, and policy makers have a clear understanding of which of these strategies may prove the most effective means of improving the competitiveness of Canadian dairy farmers. Defining methods to improve competitiveness, however, first demands a clear metric of what is required in order to become "competitive."

Typically, studies that compare competitiveness across regions use various measures of economic performance, such as production cost or productivity growth. With regional, cross-sectional, aggregate data, these studies attempt to identify the factors that cause performance to vary across dairy farms located in different provinces or states (National Dairy Policy Task Force; Jeffrey; Barichello and Stennes; Richards). Such comparisons, however, are fraught with difficulties as they rely on data often collected for different

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purposes. Further, with the continuing regulation of both the domestic Canadian and U.S. markets, differences arising through these comparisons may be more a reflection of optimal responses by producers to incentives created by policy rather than fundamental differences in performance. Consequently, studies that focus on the factors contributing to the performance of farms within a given region provide a more relevant analysis of how they are likely to fare in a more open market. Defining economic performance in terms of technical efficiency, or the ability to produce a maximum amount of output from a given set of inputs, Romain and Lambert (1994a, b), and Weersink, Turvey, and Godah present a useful set of benchmarks for producers by identifying the factors that contribute to economic performance in samples of eastern Canadian dairy farms.

However, estimates of efficiency are also imperfect measures of true economic performance for several reasons. First, there are many definitions of efficiency, including technical, allocative, scale, or overall economic efficiency (Kumbhakar). Second, there are many ways to estimate any single type of efficiency. Deterministic frontiers, stochastic frontiers, or nonparametric programming methods are all common in the literature (Kalatizandonakes and Dunn). Third, within each estimation method, choice of functional form or the structure of the error term can cause different efficiency measures or efficiency rankings for a single observation (Greene). Even if a definitive measure of efficiency can be found, there are other measures of performance that may produce different conclusions. For example, in comparing the performance of cooperative and investor-oriented milk processors, Parliament, Lerman, and Fulton used a variety of financial ratios to show that cooperative processors perform at least as well as investor-oriented firms; conversely, Ferrier and Porter found the opposite by comparing estimates of their technical efficiency. Therefore, economic performance, in the broadest sense, is best defined as a latent variable for which there exist many imperfect indicators.

In recent years, a number of studies have emerged that explicitly recognize the latency of many variables for which proxy variables had been used in the past: "taste" in demand analysis (Gao and Shonkwiler), "quality" in health care (Gertler), "managerial ability" among farmers (Ford and Shonkwiler; Kalaitzandonakes and Dunn), or personal discount rates in the determination of housing prices (Robins and West), to name a few. By using covariance relationships among observable "indicator" variables, exogenous "cause" variables, and latent constructs, the multiple-indicator, multiple-cause (MIMIC) model of Joreskog and Goldberger provides a means of both identifying latent-variable indices and estimating the impact of various factors on these indices (Joreskog and Goldberger; Anderson; Bollen).

In this analysis, we employ the MIMIC technique to recover an index of economic performance for a sample of dairy farmers in the province of Alberta, and to determine which strategies or farmer characteristics are most consistent with a high level of economic performance. Because we cannot directly measure the quality of these strategies (i.e., a producer's feed program, breeding program, or labor input), the structural latent variable method permits the construction of indices of improvement in each of these areas using variables that would otherwise be included as proxy variables. Empirical definition of these strategies is therefore the primary objective of this study.

Achieving this objective requires a two-stage empirical procedure. In the first stage, Kopp and Diewert's dual cost frontier decomposition method is used to obtain estimates of technical and allocative efficiency levels for individual producers. In the second stage,

these efficiency estimates are treated as imperfect indicators of each producer's latent economic performance in the MIMIC model framework. In order to explain variation in economic performance, the model also consists of a structural equation that relates performance to a set of "cause" variables. This set includes herd size, average milk yield, operator age, and latent measures of the quality of a producer's breeding and feeding programs and labor input. These input quality variables are, in turn, measured by a set of observable indicator variables taken from farm operating records, such as breeding expense, labor input per cow, and a variety of others. The extent to which each latent quality variable can affect economic performance is assessed using statistical tests.

Canadian Dairy Performance

The definition of economic performance in the dairy sector, as with any other industry, is contentious and subject to interpretation. Nevertheless, research on the determinants of performance often has a significant influence on the policy debate surrounding dairy issues (National Dairy Policy Task Force). Much of the research in this area has relied on aggregate, cross-sectional comparisons across regions to determine the factors that lead to production cost advantages. For example, Barichello and Stennes, and Jeffrey compare dairy production costs across provinces and conclude that larger herd sizes and higher yields are responsible for relatively low production costs. Romain and Lambert (1994a,b) extend this analysis with farm-level data to demonstrate that individual producer technical efficiency is a critical factor in the explanation of differences in production costs among dairy producers in Quebec and Ontario. However, these analyses do not account for the fact that technical efficiency and production costs are determined simultaneously, so the results are of limited practical value.

An alternative approach is to focus on efficiency alone and examine the relationship between managerial characteristics or farm endowments and various definitions of efficiency. The majority of these studies center their investigations on dairy farms in the U.S. (e.g., Bravo-Ureta; Bravo-Ureta and Rieger 1990, 1991; Grisley and Mascarenhas; Kumbhakar, Biswas, and Bailey; Kumbhakar, Ghosh, and McGuckin; Tauer; Tauer and Belbase) or eastern Canada (e.g., Weersink, Turvey, and Godah; Fan, Li, and Weersink). However, little evidence exists concerning the relationships associated with managerial factors, farm characteristics, and the performance of western Canadian dairy farms.

Productive Efficiency:
Definition and Discussion

Rigorous empirical investigations of firm efficiency find their roots in the pioneering work of Farrell. Farrell's decomposition of overall economic efficiency into technical and allocative components is well understood, and so is only briefly reviewed here. Technical efficiency is defined as the ability of a producer to achieve the maximum output possible from a given set of inputs. Allocative efficiency refers to the producer's ability to respond to economic signals and choose optimal input combinations (i.e., proportions) given relative input prices. Economic efficiency is the product of technical and allocative efficiency.

Estimates of technical efficiency typically begin with specification of a stochastic production frontier based on concepts developed by Aigner, Lovell, and Schmidt, and by Meeusen and van den Broeck. However, analyzing efficiency from a dual cost frontier perspective (Schmidt and Lovell) may be preferable for several reasons. First, estimating a cost frontier does not require an assumption that producers maximize expected profit (Zellner, Kmenta, and Dreze), typically made to justify input exogeneity in a single-equation production frontier framework. Adopting a dual cost frontier approach requires a more reasonable assumption of input price exogeneity. Also, since milk production in Alberta is controlled by a system of supply-management quotas, assuming that farmers minimize cost subject to a fixed output constraint is a more plausible behavioral assumption (Moschini). A cost frontier approach is also preferred due to problems of multicollinearity in estimating production frontiers (Kopp and Diewert), the ability to estimate efficiency in the presence of multiple outputs (Coelli), and to permit separating efficiency into its technical and allocative components (Kumbhakar).[1]

Because of these advantages, we employ a composed-error cost frontier. Schmidt and Lovell define such a frontier cost function as follows:

$$(1) \qquad C_i = C_i(\mathbf{w}, y, \beta) + (v_i + u_i),$$

$$v_i \sim N(0, \sigma_v^2) \quad \text{and} \quad u_i \sim |N(0, \sigma_u^2)|,$$

where $\mathbf{w}$ is a vector of input prices, y is output, and the overall error term is decomposed into two parts, v_i and u_i. Deviation from the frontier due to random events is represented by v_i. Inefficiency is captured by the specific, one-sided distribution of u_i with higher values of u_i representing greater deviations from minimum cost, and hence greater inefficiency. As shown in (1) above, we assume u_i to be distributed half-normal, and define $\lambda = \sigma_u/\sigma_v$, and $\sigma^2 = \sigma_v^2 + \sigma_u^2$. Jondrow et al. provide a convenient means by which the firm-specific inefficiency term may be recovered. Namely, the distribution of u_i, conditional on the value of ϵ_i, is characterized by:

$$(2) \qquad E[u_i | \epsilon_i] = \frac{\sigma\lambda}{(1 + \lambda^2)} \left[\frac{\phi(\epsilon_i \lambda/\sigma)}{\Phi(-\epsilon_i \lambda/\sigma)} - \frac{\epsilon_i \lambda}{\sigma} \right],$$

where $\epsilon_i = u_i + v_i$, ϕ is the standard normal density function, Φ is the cumulative normal distribution function, and all other parameters are as previously defined.

With the cost frontier defined in (1) above, any deviation is due to either random effects or overall productive inefficiency. By purging this frontier of random deviations in a manner similar to Bravo-Ureta and Rieger (1991), we produce a cost frontier where any remaining deviations are due only to productive inefficiency (i.e., technical and allocative). Consistent estimates of technical and allocative efficiency are then determined by calculating the technically and allocatively efficient input vectors. Following the approach developed by Kopp and Diewert and simplified by Zieschang, estimates of a frontier cost function are used to derive a vector of optimal input demand functions using Shephard's lemma:

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[1] As an anonymous reviewer notes, we do not adjust our input prices for variation in quality among producers.

(3)
$$\mathbf{x}^e = \frac{\partial C(\mathbf{w}^a, y^*)}{\partial \mathbf{w}^a},$$

where $\mathbf{x}^e$ denotes the technically and allocatively efficient input vector, C is a well-defined stochastic cost function, $\mathbf{w}^a$ is the vector of observed input prices, and y^* is actual output, assumed to be exogenous.

In order to assess overall economic efficiency for an individual firm, input bundle $\mathbf{x}^c$ is calculated. Bundle $\mathbf{x}^c$ has the same cost as $\mathbf{x}^e$, given observed input prices, but represents input use in the same proportions (i.e., ratios) as the actual input bundle, $\mathbf{x}^a$. Following the method used by Kopp and Diewert, $\mathbf{x}^c$ is established by solving the following system:

(4)
$$x_i^c / x_n^c = x_i^a / x_n^a, \quad \forall i = 1, 2, ..., n - 1,$$
$$\sum w_i^a x_i^c = C^a$$

for x_i^c, where x_i^a is the observed input level for the ith input, and C^a is the predicted cost of producing with an efficient input bundle. Overall economic efficiency (EE) is calculated as a ratio of vector norms between efficient and actual input bundles:

(5)
$$EE = \|\mathbf{x}^c\| / \|\mathbf{x}^a\|.$$

Since $\mathbf{x}^c$ lies below the y^* isoquant (i.e., is not a feasible input vector), it cannot represent a technically efficient input bundle. To assess technical efficiency, input bundle $\mathbf{x}^b$ is calculated. Bundle $\mathbf{x}^b$ is the vector of inputs on the efficient isoquant for observed output (y^*) that represents input use in the same proportions as the actual input bundle $\mathbf{x}^a$. Kopp and Diewert demonstrate that $\mathbf{x}^b$ is the "optimal" input vector for some unknown input price vector $(\mathbf{w}^b)$ and is obtained using Shephard's lemma while ensuring consistency with observed input ratios. Consequently, vectors $\mathbf{x}^b$ and $\mathbf{w}^b$ are calculated by simultaneously solving:

(6)
$$x_i^b / x_n^b = x_i^a / x_n^a, \quad i = 1, 2, ..., n - 1,$$
$$x_i^b = \frac{\partial C(\mathbf{w}^b, y)}{\partial w_i}, \quad i = 1, 2, ..., n$$

for x_i^b and w_i^b, where x_i^a and C are defined as before. Technical efficiency (TE) is calculated as a ratio of vector norms:

(7)
$$TE = \|\mathbf{x}^b\| / \|\mathbf{x}^a\|.$$

Finally, given that economic efficiency is the product of technical and allocative efficiency, allocative efficiency (AE) may be calculated as the ratio of vector norms for the economically efficient bundle and the technically efficient bundle:

(8)
$$AE = \|\mathbf{x}^c\| / \|\mathbf{x}^b\|.$$

In many studies, these efficiency measures are used as dependent variables in "second-stage" regressions to explain the causes of inefficiency. Typically, the explanatory variables consist of socioeconomic factors such as a farmer's age or education, or other variables describing the farming operation, including farm size or variable and fixed

input ratios (e.g., Kalirajan 1990; Fan, Li, and Weersink). In justifying this approach, the argument is made that farm-specific factors exert only an indirect effect on production through their association with inefficiency, so their effect is appropriately modeled in a two-stage procedure (e.g., Kalirajan 1991).

Coelli, however, points out the inconsistency of assuming that the inefficiency effects are independently and identically distributed in the first stage, while treating them as dependent variables in the second stage. If inefficiency is correlated with the production inputs, then estimates of both the production frontier and the inefficiency effects will be inconsistent (Kumbhakar, Ghosh, and McGuckin). These authors also make the point that the technical inefficiency index is inappropriate as a dependent variable in an OLS regression because it is one-sided or, after transformation by the Jondrow et al. method, bounded on the $(0, 1)$ interval.

Kalaitzandonakes and Dunn discuss the problems inherent in measuring both the dependent and independent variables in the second stage. They show that the effect of education on technical efficiency depends on how efficiency is measured. Not only are these efficiency measures imperfect indicators of true efficiency, but education, farm acreage, and age are also only proxy variables for knowledge, farm size, and experience. Use of these proxies in a second-stage regression is likely to bias estimates of their effect toward zero.

Several alternative methods exist for alleviating these problems. They include grouping farms by size and using nonparametric hypothesis tests to evaluate efficiency differences by group (Bravo-Ureta and Rieger 1991), allowing each input elasticity to vary by farm (Kalirajan and Obwona), or allowing the inefficiency measures themselves to vary systematically with firm-specific factors (Kumbhakar, Ghosh, and McGuckin; Reifschneider and Stevenson). These developments tend to make the single-stage estimation procedure considerably more complex and vulnerable to measurement errors in the regressors, however. Consequently, an alternative method is required that explicitly accounts for such measurement errors in explaining true economic performance and in measuring the factors that determine performance.

The fundamental problem is that performance and its true determinants are both unobservable, per se. Although many proxy variables for performance exist—financial profit, productivity growth, return to equity, or some measure of efficiency among the most popular—performance is only a theoretical construct, or a latent variable. Similarly, the quality measures of a producer's breeding strategy, feeding strategy, and labor input can only be inferred by their relationships with other, observable variables.

Joreskog and Goldberger define two general types of these observable variables: (*a*) *indicator* variables, which are imperfect measures of a latent variable, or measures of the effect the latent variable has on observable quantities, and (*b*) *cause* variables, which are exogenous factors that are believed to determine the latent variable value. The MIMIC model is a special case within the general class of structural latent variable models that can consist of many indicators of an unobservable variable, and many causes. For example, in their analysis of the determinants of residential home values, Robins and West consider three indicators of true value (appraised value, owner-estimated value, and assessed value), while using several home characteristics as cause variables (lot size, number of rooms, etc.).

In the current example, estimates of different types of efficiency form imperfect indicators of a producer's unobservable economic performance, while various farm-specific

operating ratios serve as indicators of the quality of the producer's management strategies. On the other hand, because herd size, milk yield, and operator age are felt to directly affect performance and are observable, they are included as cause variables in an explanatory, or structural equation for economic performance. By including the latent input quality indicators in this structural equation, tests of the significance of the equation's components constitute hypothesis tests regarding the determinants of economic performance.

Recently, MIMIC models have been used in a similar capacity in many applications involving farm production and farming ability (e.g., Kalaitzandonakes, Shunxiang, and Ma; Ford and Shonkwiler; Kalaitzandonakes and Dunn; Ivaldi, Perrigne, and Simioni; Ivaldi, Monier-Dilhan, and Simioni). While differing in their choice of indicator and cause variables, each of these studies employs a similar equation structure in identifying latent managerial ability.[2]

In order to describe the relationships between indicator and latent variables, and cause and latent variables, MIMIC models consist of two sets of equations: the structural equations described above and measurement equations. Adopting Bollen's notation, which has become the standard in this field, structural equations specify relationships among the set of latent variables (η), their observable causes ($\mathbf{z}$), and a random error term (ζ):

$$(9) \qquad\qquad \eta = \Phi\eta + \Gamma\mathbf{z} + \zeta,$$

where Φ and Γ are parameter vectors showing the marginal effects of the latent variables on each other and the cause variables on the latent variables, respectively. Measurement equations relate each indicator variable ($\mathbf{q}$) to the latent variables and a vector of random measurement errors (Joreskog and Goldberger; Bollen; Anderson):

$$(10) \qquad\qquad \mathbf{q} = \Lambda_q\eta + \epsilon.$$

In the measurement equations, the components of Λ_q are also known as factor-loading coefficients. Further, the error terms of (9) and (10) are uncorrelated with each other, have zero means, and have covariance matrices given by Ψ and Θ, respectively (Bollen).

These covariance matrices are central to the estimation method because they provide additional information on the relationships between cause and indicator variables that is required to identify the latent variable parameters (Φ). Whereas ordinary least squares regression finds parameter estimates by minimizing the sum of squared deviations between the fitted and observed values of $\mathbf{q}$, the fact that some of the dependent variables in a MIMIC model are unobserved makes this impossible (Gao and Shonkwiler; Bollen). Therefore, estimates of the model parameters are found instead by minimizing the difference between the sample covariance matrix of observed variables ($\mathbf{S}$) and a fitted covariance matrix ($\Sigma(\theta)$) for a parameter vector, θ. The key assumption underlying the estimation method is that the covariance matrices are equal at these parameter values so that $\mathbf{S} = \Sigma(\theta)$, or, in partitioned form:

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[2] Because the latent variable is, by definition, a theoretical construct, the subtle differences between the model used here and that found in Ford and Shonkwiler, or in Kalaitzandonakes and Dunn, are to be expected. While none of these specifications are incorrect, comparing them provides an illustration of how the latent variable definition is particular to the objectives of the analysis. Ford and Shonkwiler, for example, do not question the accuracy of net income as a measure of farm financial performance because their objective is to focus on the latency of ability and not performance.

(11)
$$\begin{bmatrix} \mathbf{S}_{qq} & \mathbf{S}_{qz} \\ \mathbf{S}_{zq} & \mathbf{S}_{zz} \end{bmatrix} = \begin{bmatrix} \Sigma_{qq}(\theta) & \Sigma_{qz}(\theta) \\ \Sigma_{zq}(\theta) & \Sigma_{zz}(\theta) \end{bmatrix}.$$

By solving (9) and (10) for reduced-form expressions of the latent variables η, and then substituting the result into (11), Bollen shows that the sample covariance matrix is indeed a function only of observable values and unobservable parameters:

(12) $$\Sigma(\theta) = \begin{bmatrix} \Lambda_q (\mathbf{I} - \Phi)^{-1} (\Gamma \mathbf{S}_{zz} \Gamma' + \Psi)[(\mathbf{I} - \Phi)^{-1}]' \Lambda_q' + \Theta_\epsilon & \Lambda_q (\mathbf{I} - \Phi)^{-1} \Gamma \mathbf{S}_{zz} \\ \mathbf{S}_{qq} \Gamma'[(\mathbf{I} - \Phi)^{-1}]' \Lambda_q' & \mathbf{S}_{zz} \end{bmatrix}'.$$

The matrix in (12) is called the "covariance structure equation" because it shows how imposing a specific structure on the covariance relationships between the latent and observable variables can serve to identify all the parameters of the system. Therefore, this matrix allows us to define a consistent estimator for all of the model's parameters—both on the observable and unobservable variables.

Specifically, the difference between these two matrices can be expressed in terms of a general class of loss functions (Browne):

(13) $$F(\Sigma, \mathbf{S}) = (\mathbf{s} - \sigma)' \Omega^{-1} (\mathbf{s} - \sigma),$$

where $\mathbf{s}$ and σ are vectors of the nonredundant elements of their corresponding symmetric matrices, and Ω is a positive-definite weighting matrix. Given an assumption of multivariate normality for the observed variables, Ivaldi, Monier-Dilhan, and Simioni explain that minimizing the specific form of F,

(14) $$F(\Sigma, \mathbf{S}) = \log|\Sigma| - tr(\mathbf{S}\Sigma^{-1}) - \log|\mathbf{S}| - n,$$

is equivalent to maximum likelihood, where n is the number of observations. An explanation of the specific form of each structural and latent variable equation, as well as the frontier cost function specification itself, is provided in the following section.

Empirical Models

Specification of a dual cost function provides all the information required to estimate economic efficiency (Kopp and Diewert). Of all theoretically plausible nonhomothetic, flexible functional forms, we use a Cobb-Douglas cost function.[3] Although this is a simplistic representation of Alberta dairy technology, the Cobb-Douglas functional form is parsimonious and has been widely used (Schmidt and Lovell; Kumbhakar). Following the general specification in (1), the cost frontier is written:

(15) $$\log C(y, \mathbf{w}) = \log(\beta_0) + \sum_i \beta_i \log(w_i)$$
$$+ \sum_j \alpha_j \log(z_j) + \gamma \log(y) + (v + u),$$

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[3] Despite the appeal of the translog form used by Kopp and Diewert, the translog frontier estimated in this study violated concavity, and consequently could not be solved for the optimal input levels.

where w_i is the price of the ith variable input, z_j is the jth fixed input, y is the output of milk per cow, and $(v + u)$ is the composed error term described earlier. Given the input prices included in the specification, cost or $C(y, \mathbf{w})$ is defined as total operating cost per cow, thus excluding any fixed capital costs.

As noted previously, the cost frontier is purged of random variation by adding v to cost, so that any remaining variation is due to inefficiency alone. The cost frontier, in combination with observed input levels and prices, is used to determine economically and technically efficient input vectors for each sample observation based on the calculations described earlier. Each efficiency index (AE, TE, EE), given existing input ratios, is then determined by calculating the ratio of vector norms described earlier. These indices are indicators of the latent economic performance variable, while a set of operating ratios represent indicators of the latent feeding, breeding, and labor quality variables.

Consistent with the general structure of equations (9) and (10), the empirical MIMIC model consists of a set of equations that relate unobserved performance to a set of cause variables and latent input quality variables (structural equations), and another set that relates each of the latent constructs to observable or indicator variables (measurement equations). Because this model consists of only one endogenous latent variable, performance (*PERF*), there is only one structural equation:

$$(16) \qquad PERF = \Gamma_1 X_1 + \Gamma_{11} X_1^2 + \Gamma_2 X_2 + \Gamma_{22} X_2^2 + \Gamma_3 X_3$$
$$+ \Gamma_4 BREED + \Gamma_5 FEED + \Gamma_6 LABOR + \zeta,$$

where X_1 is herd size, X_2 is milk yield per cow, X_3 is the producer's age, and *BREED*, *FEED*, and *LABOR* are latent variables representing the quality of a producer's breeding program, feeding program, and labor inputs, respectively. These cause variables—herd size, milk yield, and operator age—are selected to measure both farm and farm operation characteristics that are likely to reflect differences in performance among farmers. The latent input quality variables, on the other hand, are intended to capture each element of the debate outlined in the introduction regarding the most effective means of improving economic performance (Kennelly).

This debate centers on the roles of genetic advancement, scientific ration formulation, improved dairy supplements, larger herds, and labor-saving technological advances as means by which dairy producers have been better able to achieve a broad set of managerial performance measures. Each of these latent input quality measures is measured by a set of observable variables calculated from the Alberta Agriculture/Alberta Milk Producers' Society cost-of-production survey data. In particular, breeding expense per cow, breeding expense per liter of milk output, and the ratio of heifers and calves to cows in the herd (Ford and Shonkwiler) serve as indicators of the increased sophistication in dairy breeding.

We expect a positive relationship between each of these variables and breeding quality as more expensive sires are used in a producer's herd, and as the producer retains more quality breeding stock. The quality of a producer's feeding program is measured by the ratio of concentrates to forage, total feed cost per liter of output, and the amount of concentrates per liter of output. Again, each of these indicators is defined to represent a positive relationship with not just feed quality, but the quality of the entire feeding program.

Similarly, indicators of labor quality consist of the ratio of capital to labor, the amount of labor per liter of output, and the amount of labor per cow. While labor efficiency should rise in the capital-to-labor ratio, improvements in labor utilization should lead to lower values of the other two ratios, reflecting improvements in dairy milking and feeding technology.

In summary, the measurement model described here is given by the set of indicator equations:

$$(17) \qquad\qquad\qquad \mathbf{q} = \Lambda\eta + \epsilon,$$

where $\mathbf{q}$ is a $\{12 \times 1\}$ vector of indicators, η is a $\{4 \times 1\}$ vector of latent variables, ϵ is a $\{12 \times 1\}$ vector of errors, and Λ is a $\{12 \times 4\}$ block-diagonal matrix of coefficients to be estimated. Note that the first element in each subvector of Λ is normalized to 1.0 for estimation purposes in order to scale the latent variable values. Prior to estimating this model, we also apply a logistic transformation to each of the efficiency indicators (as suggested by Weersink, Turvey, and Godah) to account for the fact that these values are bounded between 0 and 1.[4] In comparing (16) and (17), the difference between causal and indicator variables may appear arbitrary. However, categorizing the explanatory variables as either cause or indicator variables depends upon the expected direction of causality (Gao and Shonkwiler). While cause variables lead to changes in the latent variable, indicators reveal that these changes are likely to have occurred. Ultimately, the choice of cause and indicator variables is constrained by the available data.

Data

The data for this study are from the Alberta Agriculture/Alberta Milk Producers' Society annual cost-of-production surveys from 1989–91. The sample consists of an unbalanced panel of Alberta fluid milk producers chosen by Alberta Agriculture officials in such a way to be representative of each region and herd size group.[5] The resulting sample consists of 181 pooled observations.[6]

Variable input prices used in estimating the dual cost frontier include prices for grains and concentrates, forage (i.e., hay, silage, and pasture), and hired labor. Feed prices are determined by dividing total feed expenditures by the amount fed to provide the average price per metric ton for the particular producer. Expenditures for homegrown feed are calculated using regional average prices, whereas purchased feeds are valued using local market prices. Given the geographical diversity of producers, differences in local feed markets, and differing proportions of homegrown and purchased feeds used by producers, a significant amount of both cross-sectional and time-series price variation exists in the sample. The price of labor is calculated as the total cost of

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[4] As Weersink, Turvey, and Godah explain, this transformation is necessary since each dependent variable is bound on the [0, 1] interval. Estimating these equations without taking censoring into account leads to parameter bias.

[5] The purpose of the cost-of-production survey is to allow the Public Utilities Board (PUB) in Alberta to conclude whether the formula-determined fluid milk price is providing producers with excessive rates of return. Therefore, both Alberta Agriculture economists and the Alberta Milk Producer's Society have incentives to ensure that the sample is indeed representative of the population of milk producers.

[6] An initial version of the model was estimated in which the cost function parameters were allowed to vary by year. Likelihood-ratio tests were used to test the null hypothesis that there were no significant differences between these and time-invariant parameters. We failed to reject the null hypothesis, so the final model was estimated using pooled data.

hired labor plus family labor, divided by total hours. Due to a lack of worker training or experience data, the wage is unadjusted for quality.

Total cost is defined as the weighted sum of expenditures on these variable inputs for the dairy enterprise. As such, it includes expenditures for activities not directly related to producing milk, such as raising calves to milking age. Total enterprise costs are divided by the herd size to obtain a cost per cow.

The cost frontier is defined as a short-run, or variable cost frontier. Observed cost levels are therefore conditional on existing capital stocks. Several inputs may be classified as being fixed, such as capital, herd size, and quota holdings. However, the estimated cost frontier includes only capital as a fixed factor. Capital consists of the value of buildings and equipment specific to the dairy enterprise. Ball's method provides an annual capital rental price series.[7] The rental price is then used to derive an annual capital quantity level from reported stock values. Herd size is excluded, as costs are measured on a per cow basis.[8] Quota is excluded as a fixed variable because its inclusion would lead to near, but not perfect, multicollinearity with milk output.

The dual cost function is also conditional on the level of quota-regulated output (Moschini). Output consists of the total amount of milk shipped from the farm to both the fluid and industrial markets in hectoliters (hl.) per cow per year. Although the producers in the Alberta Agriculture survey are largely fluid milk producers, all must hold some industrial (market-sharing) quota in order to sell milk produced in excess of their utilized fluid allocation.

While not included as a fixed factor in the cost function analysis, herd size is included as a cause variable in the structural equation for the latent performance construct in the MIMIC model. However, the pace of genetic progress in dairy cows has been rapid enough that cattle from two different vintages are two qualitatively different inputs. Therefore, herd size for each observation is "deflated" by an index of genetic progress to incorporate the influence of technological (genetic) improvement in dairy cattle. As a result of this adjustment, the herd size included as the cause variable represents the number of genetic equivalent-cattle livestock inputs. The index used to deflate the observed herd size is the provincial breed class average (BCA) for Holstein cattle. Annual changes in the provincial BCA represent improvements in milk productivity which are at least partly attributable to genetic progress. Unfortunately, the BCA index is also affected by feeding and other management practices. Nevertheless, the BCA is the best available proxy for a true measure of exogenous genetic improvement.

The other indicator variables (i.e., breeding expense, calf- and heifer-to-cow ratio, capital-to-labor ratio, labor productivity ratios, ratio of grain and concentrate expense to forage expense, and the concentrate productivity ratios) are taken or calculated directly from the survey data.[9] Susko offers a more detailed description of the survey instrument and input classifications. Table 1 provides summary statistics for some of the relevant survey variables. All monetary values are expressed in Canadian dollars.

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[7] Specifically, Ball derives an annual user cost series for each capital stock. A user cost for dairy capital is found by summing the opportunity cost of capital (average interest rate on debt financing multiplied by the reported book value of employed capital), the annual amount of depreciation calculated at straight line rates consistent with current tax code, annual expenditures for maintenance of dairy capital, and expenditures for rental services.

[8] Since the analysis is done on a per cow basis, the "fixed" factor would be the value of the individual cow. Because cow numbers are expressed in equivalent-cattle livestock units (discussed below), each cow has basically the same value.

[9] The breeding expense variable is taken from a single account from the survey data that includes both breeding and veterinary expense. Therefore, increases in the value of this variable may be attributable either to improvements in a producer's breeding program or to a deterioration of herd health.

Table 1. Summary Statistics from the Alberta Dairy Cost-of-Production Survey, 1989–91

Variable	Units	Average	Standard Deviation	Minimum Value	Maximum Value
Milk Output	hectoliters/cow	67.13	11.79	33.72	118.45
Grain and Concentrates	metric tons/cow	3.64	1.01	1.78	7.62
Hay and Forage	metric tons/cow	6.64	2.03	2.07	13.67
Hired Labor	hours/cow	28.64	25.15	0.07	160.91
Family and Operator Labor	hours/cow	62.93	28.17	3.70	134.36
Capital	$/cow [a]	3,859.30	1,672.11	196.17	8,483.56
Quota	liters/day	897.86	817.21	285.00	9,445.00
Herd Size	cows/farm [b]	65.94	35.65	24.50	214.50

[a] This figure represents the "stock" of capital, rather than the "flow" (i.e., capital usage) calculated for use in the production function estimation procedure. Monetary values are in Canadian dollars.

[b] Cattle numbers in the analysis have been "corrected" for embodied technological change by scaling them using annual breed class average (BCA) values. These values are true, or uncorrected herd sizes.

Results and Discussion

Although the focus of this section is on investigating the determinants of economic performance in Alberta dairy production, the cost structure is of some interest. Table 2 provides both OLS estimates of a Cobb-Douglas cost function, and maximum-likelihood estimates of a Cobb-Douglas cost frontier. Because the parameter estimates differ very little quantitatively, nothing is lost by interpreting the structure of Alberta dairy production in terms of the cost frontier. The cost frontier is first evaluated for consistency with concavity and monotonicity. Upon examination of the Hessian for the estimated cost function, it is determined to be concave. Monotonicity holds if each input demand is nonnegative. This condition is evaluated at the mean of each variable using the input demands given by:

$$(18) \qquad x_i(\mathbf{w}, y, z) = \beta_0 \beta_i (y^\gamma z^\alpha w_i^{\beta_i - 1} \Pi w_j^{\beta_j}), \quad \forall \, i \neq j.$$

This condition is satisfied for all inputs.

The specific parameter estimates for the cost function provide insights into the cost structure of the Alberta dairy sector. The results suggest slightly increasing returns to scale, with the scale elasticity being equal to 1.114 (standard error = 0.0675).[10] However, constant returns to scale cannot be rejected statistically. In addition, the own-price elasticities for labor, concentrates, and forage are -0.815, -0.881, and -0.561, respectively.

These results may be compared with the elasticities reported by Moschini for Ontario dairy farms.[11] Similar to the Alberta results, Moschini reports increasing returns to scale for most farm sizes. He also determines the demand elasticity for feed (concentrates and

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[10] Given the Cobb-Douglas functional form, the scale elasticity is equal to the inverse of the milk output coefficient (Beattie and Taylor) and is consistent with economies of size in milk production.

[11] Moschini's results are not directly comparable to those reported here, as he estimates a cost function rather than a frontier. However, his study remains the seminal discussion of the structure of dairy costs under Canadian supply management.

Table 2. Frontier Cost Function for Alberta Milk Production (OLS and Maximum-Likelihood Methods)

| | Milk Cost Frontier Estimates | | | |
| | OLS | | Maximum-Likelihood | |
Variable	Coefficient	t-Ratio	Coefficient	t-Ratio
Constant	2.3479	3.0754*	1.8893	2.2176*
Wage	0.2272	1.9318*	0.1853	1.2633
Grain Price	0.0934	1.9223*	0.1190	2.7591*
Forage Price	0.4495	3.4897*	0.4391	3.0471*
Capital	0.0508	2.5485*	0.0490	2.6022*
Milk Output	0.8838	12.7476*	0.8976	13.2891*
σ_u/σ_v	—		1.7468	4.4637*
$\sqrt{\sigma_v^2 + \sigma_u^2}$	—		0.2045	8.3546*
R^2	0.6316		Q-R^2	0.6732
$F_{5,175}$	60.2600		N	181.0

Notes: An asterisk (*) denotes statistical significance at the 5% level for a one-tailed test. The Q-R^2 value is the coefficient of determination between observed and predicted cost values.

forage combined) to be -0.656, which is comparable to the individual elasticities for Alberta producers. However, the elasticity of labor demand from Moschini's study (-0.219) is far lower (i.e., more inelastic) than the value reported in the current study.

Also of interest is the distribution of efficiency by herd size. The dual cost frontier is used to derive indices of allocative, technical, and overall or economic efficiency for each producer using Kopp and Diewert's method, described earlier.[12] Summary statistics for these indices are presented in table 3. The average level of economic efficiency calculated over all farms in the sample is 90.6%, the average level of allocative efficiency is 96.3%, and the average index of technical efficiency is 94.2%. While no normative conclusions can be drawn from this latter result on its own, this level of technical efficiency is higher than that reported by previous studies. Among dairy efficiency studies reviewed by Ahmad and Bravo-Ureta, average indices of technical efficiency vary from a high of 90% for Argentinean dairy farms (Schilder and Bravo-Ureta) to a low of 65% among a sample of Utah dairy farms (Kumbhakar, Biswas, and Bailey).

Table 3 also provides an indication of the distribution for each measure across farm size. Taken in isolation, these measures of technical, allocative, and economic efficiency appear to be very similar among herd size groups. However, specific tests of the relative effect of herd size and efficiency on economic performance are more relevant and are obtained through the structural latent variable model. The results presented in table 3 may be an indication, however, of a high degree of homogeneity within the Alberta dairy sector.

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[12] Strictly speaking, Kopp and Diewert's method of calculating efficiency measures does not mathematically impose the [0, 1] bound on technical efficiency. However, because this bound is conceptually correct, the efficiency measures in table 3 are scaled accordingly.

Table 3. Frequency Distribution of Efficiency Indices by Herd Size: Alberta Dairy Production

Herd Size	N	Technical Efficiency		Economic Efficiency		Allocative Efficiency	
		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
20–40	27	0.9412	0.0094	0.9048	0.0203	0.9615	0.0238
41–60	80	0.9403	0.0100	0.9068	0.0205	0.9645	0.0234
61–80	41	0.9388	0.0073	0.9063	0.0226	0.9654	0.0226
81–100	12	0.9476	0.0185	0.9088	0.0272	0.9593	0.0333
101–120	4	0.9605	0.0268	0.8922	0.0407	0.9295	0.0501
121–140	7	0.9524	0.0217	0.9089	0.0097	0.9547	0.0244
141–160	4	0.9441	0.0008	0.8964	0.0072	0.9495	0.0071
161 +	6	0.9468	0.0006	0.9170	0.0035	0.9687	0.0031
N	181	0.9418	0.0117	0.9064	0.0218	0.9626	0.0253

Since performance and each of the latent input-quality variables are inherently unobservable, estimates of the factors contributing to these variables are determined by using the structural latent variable (MIMIC) model. Tables 4 and 5 present the results obtained by estimating both the indicator (i.e., measurement) and latent variable (i.e., structural) equations, respectively. As described above, measurement equations serve to scale and identify each latent variable, thereby purging each of as much measurement error as possible. Further, in order to identify the system, one coefficient for each latent construct must be normalized to 1.0, two in the case of performance. Beyond identifying each latent variable, parameter estimates for the nonnormalized measurement equations, also known as factor-loading coefficients (Ford and Shonkwiler), provide valuable information as they indicate how each latent variable is related to its observable indicators.

For example, the results in table 4 show that breeding quality rises in breeding expense per cow. However, the way this variable is defined, the indicated quality may rise if an operator purchases higher quality bulls through artificial insemination programs, improves the level of attention paid to herd health, or, conversely, experiences reproduction problems requiring greater veterinary attention. By controlling for the effect of breeding expense per unit of output, we account for this possibility. Further, by normalizing on the ratio of calves and retained heifers to cows, we ensure that this index rises in the quality of a producer's breeding program. With respect to the latent feeding-program-quality variable, indicated quality rises in the cost per unit of milk output, while accounting for the effect of differing grain-to-forage ratios among the sample herds. This result is as expected. Similarly, the quality of a producer's labor input rises in the amount of labor used per cow, and falls in an inverse measure of partial labor productivity while controlling for differences across farms' capital-to-labor ratios. Moreover, it is important to note that in each case the factor-loading coefficients are statistically significant.

Likewise, the statistical significance of performance in the measurement equation for overall economic efficiency is an important result in itself, suggesting that efficiency is a valid indicator of the unobservable performance variable. Given the pooled time-series/

Table 4. MIMIC Model: Measurement Equations for Latent Dairy Performance

Indicator	Latent Construct	Estimated Coefficient	Var(ϵ_i)	R_i^2
Technical Efficiency [a]	Performance	1.0000	0.0004 (1.2294)	0.4389
Allocative Efficiency [a]	Performance	1.0000	0.0041* (9.5451)	0.1500
Economic Efficiency [b]	Performance	0.8901* (50.5284)	0.0012* (8.8131)	0.7921
Breeding Expense/Cow	Breeding Quality	0.9673* (27.3184)	1.8404* (8.6771)	0.8574
Calf/Cow Ratio	Breeding Quality	1.0000	0.0666* (7.0615)	0.9349
Breeding Expense/Output	Breeding Quality	0.9315* (23.4882)	0.6724* (8.5963)	0.8661
Grain/Forage Ratio	Feeding Quality	0.8879* (17.7423)	0.0889* (8.3853)	0.7862
Feed Cost/Output	Feeding Quality	0.4956* (7.5108)	0.0002* (8.7301)	0.7533
Concentrates/Output	Feeding Quality	1.0000	8.5858* (9.6516)	0.2456
Labor/Cow	Labor Quality	0.9931* (31.7845)	1.0174* (3.5922)	0.9868
Labor/Output	Labor Quality	0.9632 (27.2813)	0.2513* (8.4904)	0.9285
Capital/Labor Ratio	Labor Quality	1.0000	2.4623* (9.0298)	0.8619

Note: An asterisk (*) denotes statistical significance at the 5% level using a one-tailed test of significance.

[a] Technical (allocative) efficiency refers to the technical (allocative) efficiency ratio calculated using Kopp and Diewert's method.

[b] For economic efficiency, the parameter is normalized to 1.0 for identification purposes. Note that the efficiency measures form both indicators and latent constructs in this model structure.

Table 5. MIMIC Model: Structural Equation for Latent Dairy Performance

Factor/Cause	Estimated Coefficient	*t*-Ratio	Factor/Cause	Estimated Coefficient	*t*-Ratio
Herd Size	0.6071*	2.0772	Breeding	0.8061*	1.8043
(Herd Size)^2	−0.4357*	−2.5141	Feeding	−0.3062	−1.3189
Milk Yield	1.1391*	4.8002	Labor	1.1275*	4.4791
(Milk Yield)^2	−1.3972*	−2.9471	Variance (ζ)	0.0011*	6.0412
Operator Age	0.0245	0.3556			

Note: An asterisk denotes statistical significance at the 5% level using a one-tailed test of significance.

cross-section nature of this data set, each of the measurement equations provides a relatively good fit, with performance explaining more than half of the variation in overall economic efficiency. Perhaps of more direct relevance to the objectives of this study, however, are the structural equation estimates.

Specifically, these estimates provide a means of testing the core hypotheses of this analysis—namely, how each farm-specific factor or managerial strategy affects dairy performance. Before interpreting the structural parameters, it should be noted from table 5 that the variance of the disturbance term in this equation (ζ) is significantly different from zero. This suggests that the structural covariance model is a better empirical representation of performance than an equivalent regression model with each efficiency measure regressed on a set of proxy variables. The three latent input-quality variables enter the structural equation in linear form, as does operator age, while the two cause variables (yield and herd size) enter as quadratics. Yield and herd size are specified in quadratic form as it is likely there are optimal levels of both at which performance is a relative maximum. Beyond a certain point, further increases in either are likely to lead to wasted inputs and declining efficiency.

For example, the estimates in table 5 suggest that the maximum efficiency herd size in Alberta is 70 cows. Therefore, these results provide some evidence of the economic cause of the general trend toward larger herds. The evidence from other studies concerning the relationship between efficiency and herd size is mixed. The maximum efficiency herd size calculated in this study is higher than that found by Romain and Lambert (1994b) for Quebec dairy farms, but is below the maximum efficiency herd size of 102 cows calculated for Ontario dairy farms by Weersink, Turvey, and Godah. While the results from non-Canadian studies suggest, in general, a positive relationship between herd size and efficiency (e.g., Tauer and Belbase; Tauer; Bravo-Ureta and Rieger 1990, 1991; Kumbhakar, Biswas, and Bailey; Bailey et al.), the evidence is not entirely consistent (e.g., Ahmad and Bravo-Ureta; Bravo-Ureta). Perhaps with a longer time-series sample, future research employing a similar approach may be able to provide stronger statistical support for our result.

Along with average herd size, milk yields are also increasing over time. Weersink, Turvey, and Godah interpret yield as a measure of both genetic production potential and feeding program effectiveness. In their sample of Ontario dairy farms, these authors found a linear relationship between yield and efficiency with an elasticity of 0.973. For Alberta dairy farms, estimates of a quadratic yield term imply that maximum efficiency occurs at a yield of 90.3 hectoliters/cow per year. As this is more than the sample average milk yield of 67.1 hectoliters/cow (table 1), these estimates suggest that dairy performance may be improved through further increases in milk yields. Given recent trends, however, it is clear that dairy farms are rapidly approaching the level of maximum-performance yield.

The results in table 5 further indicate that farmers may also improve their performance through improving the quality of their breeding programs and the quality of their labor input, but not necessarily through their feeding programs. Table 5 shows a point estimate of a marginal increase of 0.806 for an increment to a farmer's breeding program, which is scaled to represent the response to a marginal increase in breeding expense per cow of one dollar. This result is broadly consistent with the findings of Romain and Lambert (1994a) for both their Ontario and Quebec data.

Labor quality, on the other hand, is shown to contribute significantly to performance for Alberta dairy farms. In general, this result is also consistent with the findings of Romain and Lambert (1994a), who use the ratio of labor to capital for Ontario and Quebec dairy farms as a proxy variable for labor productivity. Specifically, they found that technical efficiency is directly related to the degree of labor intensity. In this study, the latent labor quality variable rises in both labor per cow and in labor per unit of output while normalizing on the amount of capital per cow, thus measuring labor productivity directly. Although they do not use a measure of relative input intensity, Weersink, Turvey, and Godah found that more highly capitalized farms are less technically efficient as efficiency falls in the total value of buildings per cow.

While performance rises in both breeding and labor productivity, the results in table 5 show that performance falls in the quality of a producer's feeding program, although the relevant parameter is statistically significant only at a confidence level lower than conventionally accepted. Combining this result with the measurement equation estimates in table 4, the feed quality index rises in both the proportion of concentrates used and the overall cost of feed used per unit of output. This suggests that more expensive feeds do not necessarily improve efficiency. This conclusion is consistent with that of Weersink, Turvey, and Godah who found that efficiency falls in the ratio of feed purchased off-farm, indicating homegrown feed is of higher quality. Romain and Lambert (1994a) reported that Quebec dairy efficiency increases with the caloric content of feed, and is inversely related to the ratio of forage to concentrates. Our table 4 results disagree with Romain and Lambert in that Alberta dairy performance decreases in the opposite ratio—i.e., concentrates to forage. Again, however, this result is statistically insignificant at conventional levels.

While many studies also include education or experience as an explanatory variable for economic performance, the results in table 5 suggest that experience does not exert a significant influence on efficiency. This finding is consistent with the earlier studies of Tauer and Belbase, and Weersink, Turvey, and Godah, but differs from Romain and Lambert's (1994a) observation that higher levels of education cause greater efficiency levels among Quebec dairy farmers. Perhaps by accounting for the effectiveness of all other strategies that should be positively related to a producer's level of managerial skill, the effect of experience and education is already captured by these other variables.

Conclusions

Empirical definitions of economic performance abound in the literature, including production costs, productivity growth, or various measures of technical, allocative, and overall efficiency. One common feature of all of these measures, however, is that they are each imperfect indicators of a variable that is inherently unobservable—economic performance. In this study, we use a structural latent variable approach to investigate the determinants of economic performance in Alberta dairy production. With this multiple-indicator, multiple-cause (MIMIC) model, measures of technical, allocative, and economic efficiency comprise a set of performance indicators, while causes of the latent variable consist of herd size, milk yield, capital/labor ratio, concentrate/forage ratio, operator experience, and breeding expense per cow. By minimizing the distance between sample and predicted covariance matrices, this method provides unbiased

estimates of the effect of each cause variable on performance. Kopp and Diewert's method of decomposing economic efficiency into allocative and technical components provides the means by which the indicators are calculated from estimates of a dual stochastic cost frontier.

Estimates of efficiency using a farm-level panel data set of Alberta dairy farms find the average dairy farmer to be highly efficient relative to the best farmers in the industry. While this result cannot be used to compare efficiency levels with producers in other dairy industries, it does suggest that Alberta dairy farmers are relatively homogeneous compared to groups of dairy producers studied elsewhere. Estimates of the MIMIC model provide an indication of the factors that are important to Alberta dairy farm performance, and those that are not. Unlike previous results for Quebec dairy found by Romain and Lambert (1994a,b), neither an operator's investment in human capital nor the quality of feed appear to explain Alberta dairy performance. Further, modeling the effect of herd size on performance as a quadratic results in a maximum efficiency herd size of approximately 70 cows, which is somewhat larger than Romain and Lambert's (1994b) optimal Quebec herd size, but below the optimal herd size in Ontario reported by Weersink, Turvey, and Godah. Given that this herd size for Alberta is below the sample average, it may be that Alberta dairy producers are improving performance through other means. Further gains in performance through higher yields are possible, because the sample average of 67.1 hectoliters/day is considerably lower than the optimal yield of some 90 hectoliters/day.

Alternatively, Alberta dairy performance may rise with further investment in breeding and veterinary services, and/or greater capital intensity. Careful attention to herd health, improved heat detection, and reduced incidence of mastitis and other common afflictions all require a greater investment in veterinary services, while adopting an artificial insemination program, transferring embryos, or simply using more expensive bulls all increase breeding expenses. These methods are associated with greater cow longevity and genetic production potential—both critical factors in determining economic performance.

Labor productivity is also important in dairy, as labor costs constitute approximately 22% of total production cost (Susko). Given more efficient milking technology, feed management techniques, and manure handling methods, capital investment is likely to lead to higher labor productivity, and consequently to improvements in overall economic performance. A fruitful avenue for future research may consider the role of dairy policy, namely supply management, on the incentive for farmers to invest in such productivity-improving technology.

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