The Optimality of Input Allocations by Massachusetts Dairy Farmers

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Dairy farmers faced sharply declining milk prices and rising input costs during 1991 (National Milk Producers Federation), making careful allocations of input expenditures crucial for farm survival. Under these conditions, farmers realize the need for forward planning to find the most profitable organization of available resources. Farm planning requires information on industry standards on optimal allocations of input expenditures. The focus of this study is to show that farm survey data can be useful in deriving these industry standards.

We address two issues related to the use of farm survey data in this paper. The first is the usefulness of summary and average statistics from farm survey data as standards or *benchmarks* for farm cost and return planning. Although neoclassical microeconomic theory is very specific about optimal input allocation, practical application of these concepts is difficult. As Levins argues, it is unlikely that farm operators solve first-order conditions to determine optimal input levels. If farmers are not solving equations to determine optimal input levels, then how do they decide? They frequently use whole farm and enterprise budgets in decision making. Publications showing average levels of farm costs and returns, often calculated from farm survey data, are widely available and are commonly used as standards to develop budgets. These *benchmarks* and resulting budgets may not reflect the best use of resources if input allocations reported in the farm surveys were not optimal for farms surveyed. For example, if most dairy farmers try to maximize output per cow rather than profits, then average input expenditures would be too high. Budgets based on such farm survey data would suggest that farmers produce beyond profit maximization levels. We use regression analysis in this study to determine whether input expenditure allocations by dairy farmers are appropriate for profit maximization.

The second issue is meaningful analysis of farm survey data when important economic information is missing. Farm survey data provide a rich source of information. However, the ability of researchers to statistically model optimal input allocation decisions is limited. For instance, farm survey cross-sectional data have been used to estimate both primal and dual models of production. Dual applications to the dairy sector include studies by Weaver and Lass and Stefanou and Saxena. In both cases, detailed price data were available allowing estimation of dual profit functions. Farm survey data usually lack information on input prices and quantities but provide information on revenues and expenditures. For example, the USDA Farm Costs and Returns Survey provides detailed revenue and expenditure data but does not report specific prices. In addition, getting meaningful measures for aggregate quantities and prices is difficult even if specific price and quantity data are available. A multitude of inputs are used on any given farm, making aggregation necessary for statistical modelling.

An alternative to the dual approach is estimation of the production function in value form. In his article, Griliches estimated an agricultural production function using cross-sectional data. Zellner et al. and Just et al. discussed the appropriateness of estimating production functions from cross-sectional data. Cross-sectional production function analyses have primarily focused on technical efficiency using frontier production function methods. Technical efficiencies of dairy farms were considered in Maine and Vermont (Bravo-Ureta), Pennsylvania (Grisley and Mascarenhas), and New York (Tauer and Belbase). However, researchers have not addressed efficiencies of individual input allocations.[1] Analysis of individual input allocations requires evaluation of marginal products relative to input prices which are usually not available.

In this study, we develop a convenient test of optimal input allocations. We used cross-sectional data on farm costs and returns for a sample of Massachusetts dairy farms in regression analysis to determine whether input allocations are consistent with profit maximization. We then used a random coefficients regression model to provide information on optimal input expenditure allocations by individual farm operators. We also investigated the relationship between farm profitability and input allocation.

Conceptual Framework and Empirical Model

The usual neoclassical assumption for producer behavior is to maximize profits or minimize costs. Duality theory suggests that profits or costs are functions of exogenously determined netput (output and variable input) prices and quantities of fixed factors. However, data limitations (for example, absence of netput prices) may not allow the specification of such functions. This study suggests the use of net returns, defined as gross revenue minus input expenditures. Given the small geographical area and cross-sectional nature of the data used in this study, we assumed that Massachusetts dairy farmers face similar output and input prices. In addition, we assumed that farmers, based on their knowledge of dairy price support policy, determine their output levels *a priori* and try to maximize profits based on the optimal use of inputs. This behavioral assumption is similar to a cost minimization framework where the producer sets a target output level and minimizes cost (or maximizes profits) by determining optimal allocation of inputs. Profits or net returns are then largely determined by optimal input expenditures. Since farmers face similar input prices, net returns are determined by optimal input choices. The intent is then to examine how the input allocations affect net returns.

Using farm-level data on costs and returns, we calculate profit for each farm and form the empirical model:

$$\Pi_i = \beta_o + \sum_{j=1}^{K} \beta_j E_{ij} + u_i \tag{1}$$

where Π_i are the i^{th} firm's net returns or profits, the E_{ij} are the i^{th} firm's input expenditures for the j^{th} input category, the βs are parameters to be estimated and u_i is the random disturbance. The useful aspect of the analysis is the interpretation of parameter estimates from the standpoint of production analysis. Estimated parameters show additional profits from increased expenditures on an input, all other expenditures held constant. The profit maximizing firm should increase expenditures on an input until additional returns just equal expenditures or, equivalently, the additional profit due an increase in expenditure should equal zero. Thus, all parameter estimates should be approximately zero if farmers are maximizing profits as we show in the appendix. Alternatively, farmers may have an alternative objective such as maximizing output. In fact, dairy farmers are typically well aware of output per cow as this statistic appears on most management reports. If farmers try to maximize output, then input expenditures will proceed until the additional returns are zero. As we show in the appendix, this implies parameter estimates equal to a minus one since marginal products will be zero. Thus, the model provides a simple and convenient test of farm behavior:

Profit maximization: H_o: $\beta_j = 0$ *for all j* (a)

Output maximization: H_o: $\beta_j = -1$ *for all j* (b)

From the form of the tests in (a) and (b), it is clear that joint tests of the two behavioral hypotheses are possible. We can conduct a joint test of hypothesis (a) by a simple F-test or likelihood ratio test. Similarly, the imposition of restrictions in (b) imply a joint hypothesis which we can test using F or likelihood ratio tests. Alternatively, we might allow for no consistent behavioral hypotheses across all inputs by using standard t-statistics to show whether expenditures on a particular input exceed or fall short of profit maximizing levels.

The results are of interest from the standpoint of research on firm behavior as well as Extension specialists and decision-makers. If the model performs well, specialists will be able to identify input categories where farmers are *over-spending* and those categories where farmers are *under-spending*.

Random Coefficients Regression Model

Further empirical application employing a random coefficients regression (RCR) model allows analysis of individual farm input use. In most empirical work, we estimate parameters of primal or dual functions using a fixed coefficients least squares procedure. Thus, the researcher effectively assumes that the effects of exogenous variables are constant through time or across observation units for cross-sectional data. However, a plausible alternative is to allow parameters to vary through time or across observational units. The cause of such variations may be differences in production structure, available resources, or a host of other factors that are farm specific (for example, management skill). In this paper, we allow for the possibility that profit maximizing behavior of dairy farmers may vary given different production conditions affecting each farm. Use of a fixed coefficients approach to describe input allocations of both a profitable farm and an unprofitable farm may be misleading.

Following Swamy and Tinsley, parameters of the model in equation (1) may be written as:

$$\beta_{ij} = \bar{\beta}_j + a_{ij}.^2 \tag{2}$$

In this case, we assume the parameters to be random variables drawn from a common distribution with mean $\bar{\beta}$. If we can characterize the production structure by such a behavior, we say the model is generated under a random coefficients procedure. The RCR model is often appropriate in the analysis of cross-section data (Hildreth and Houck). We assume the error term *a* to be a sequence of uncorrelated vector random variables with expected mean value of zero and a constant variance-covariance matrix denoted by $\Sigma_{\underline{A}}$ with zero off-diagonal elements. Since we do not know $\Sigma_{\underline{A}}$ and β, the Swamy and Tinsley algorithm provides for a data-based iterative estimation procedure in which $\Sigma_{\underline{A}}$ is arbitrarily chosen with zero off-diagonal elements. Through several iterations, we can derive efficient and consistent estimates of $\Sigma_{\underline{A}}$ and β. We can select the mean values, β, which provide the lowest root mean square error.

Results

We estimated the empirical model using survey data for 33 Massachusetts dairy farms for the year 1988. To account for scale economies that may exist, we adjusted the data on costs and returns to a *per cow* basis. Using data on a *per cow* basis is appealing since production per cow is a readily available measure of productivity to the farm operator. In addition to input expenditures, we included a set of fixed factors including operator labor and unpaid labor. We also included the number of cows in the model to check the effectiveness of adjusting data to a *per cow* basis. We aggregated input expenditures into eleven accounts: (1) fuels and utilities; (2) crop production; (3) business and office; (4) land; (5) total purchased feeds; (6) hired labor; (7) livestock purchases; (8) livestock supplies; (9) marketing; (10) repairs and supplies for machinery; and (11) depreciation expenditures. We present means for the variables in the data set in Table 1.

Table 1.
Descriptive Statistics for Massachusetts Dairy Farms – 1988 Survey Data

	Means per farm (N = 33)	Means per cow (N = 33)
Profits ($)	–4537.74	–53.03
Inputs ($)		
Fuels and utilities	8373.18	127.26
Crop production	13118.88	135.68
Business and office	8846.82	107.63
Land	11346.03	163.58
Purchased feeds	48433.58	631.51
Hired labor	21947.90	225.57
Livestock purchases	2886.21	29.29
Livestock supplies	3798.27	55.42
Marketing	5039.06	71.48
Machinery repairs and supplies	14665.10	212.32
Depreciation	9645.91	181.94
Fixed factors		
Operator labor (hours)	3585.37	76.56
Unpaid labor (hours)	1698.01	38.72
Herd size (number of cows)	77.58	77.58

We initially estimated the model by ordinary least squares (OLS) using the data on a *per cow* basis. The model fit the data well, explaining about 77 percent of the variation in profits per cow. Visual inspection of the errors did not suggest heteroskedasticity was a problem. White's test for heteroskedasticity, applied to both the errors and squared errors, further supported the conclusion that heteroskedasticity was not a problem. The parameter estimates and t-statistics presented in Table 2 are those of the OLS estimation.

Parameter estimates vary and do not provide a consistent indication that farmers either maximize profits ($\beta_j = 0$) or maximize production per cow ($\beta_j = -1$). Joint hypothesis tests were also inconclusive about a consistent behavioral objective for dairy farmers. We rejected the joint hypothesis of profit maximization using an F-test. We compared the calculated F value of 4.88 to the tabled value of 3.43 for the one percent level of significance. However, we also rejected the joint test of output per cow maximization at the one percent level of significance ($F_{calc} = 4.20$). Chi-squared tests provided the same conclusions at the one percent level of significance.

We present calculated t-statistics in Table 2 for the hypotheses of profit maximization ($\beta_j = 0$) and output maximization ($\beta_j = -1$). It is again clear from these results that farmers do not consistently choose input levels to either maximize profits or maximize output. The results from regressions on net returns per cow show that we would not reject the null hypothesis of profit maximization for eight of the eleven input categories: fuels and utilities; crop production; business and office; purchased

Table 2.
Estimated Regression of Net Returns per Cow on Variable Input Expenditures and Fixed Factors per Cow

	Estimated coefficients	t – Statistics	
		$H_o: \beta_j = 0$	$H_o: \beta_j = -1$
Inputs			
Fuels and utilities	–0.612	–0.309	0.196
Crop production	0.558	0.706	2.207[a]
Business and office	0.220	0.270	1.495
Land	–1.065	–2.444[a]	–0.150
Purchased feeds	–0.139	–0.466	2.890[b]
Hired labor	–0.627	–2.218[a]	1.321
Livestock purchases	–1.621	–0.999	–0.383
Livestock supplies	3.144	1.418	1.869[a]
Marketing	–0.754	–0.749	0.244
Machinery repairs and supplies	–0.825	–2.030[a]	0.430
Depreciation	–0.556	–1.505	1.202
Fixed factors			
Operator labor	1.666	1.192	NA
Unpaid labor	–3.073	–2.529[a]	NA
Herd size	–0.471	–0.549	NA

a. Statistically different from H_o: at the 5 percent level of significance.
b. Statistically different from H_o: at the 1 percent level of significance.
NA Not applicable.

feeds; livestock purchases; livestock supplies; marketing; and depreciation. However, *five* of these categories: fuels and utilities, business and office, livestock purchases, marketing, and depreciation, do not fall neatly into either behavioral hypothesis. We found that we would also not reject the null hypothesis of output maximization for these five categories. We would not reject the null hypothesis of output maximization for a total of eight of the eleven input categories. In addition to the five listed above, expenditures on land, hired labor, and machinery repairs and supplies were at output maximizing levels. The indication that Massachusetts dairy farmers are choosing at least some of their inputs so as to maximize output rather than profits is consistent with the findings of Stefanou and Saxena and Luh and Stefanou for Pennsylvania dairy farmers.

We next estimated a RCR model using the data on a *per cow* basis.[3] We present the estimated mean coefficients and asymptotic t-statistics for the mean coefficients in Table 3. We predicted coefficient estimates for individual farms using the mean vector ($\bar{\beta}$) and decomposition of the variance-covariance matrix ($\Sigma_{\underline{A}}$). The OLS and RCR results are comparable. OLS parameter estimates and the mean RCR estimates have the same sign with one exception, crop production expenditures which was not significantly different from zero in either model. Both models suggest that expenditures on hired labor and machinery repairs and supplies are more than profit

Table 3.
Random Coefficients Regression Results for Net Returns per Cow

	Estimated coefficients	t – Statistics	
		$H_o: \beta_j = 0$	$H_o: \beta_j = -1$
Inputs			
Fuels and utilities	–0.1321	–0.269	1.767[a]
Crop production	–0.0001	0.000	3.815[b]
Business and office	0.2705	1.037	4.872[b]
Land	–0.2819	–0.704	1.792[a]
Purchased feeds	–0.1561	–1.383	7.475[b]
Hired labor	–0.2981	–3.160[b]	7.443[b]
Livestock purchases	–1.8416	–3.114[b]	–1.423
Livestock supplies	1.4113	2.009[a]	3.432[b]
Marketing	–0.4411	–1.011	1.281
Machinery repairs and supplies	–0.3377	–2.356[a]	4.622[b]
Depreciation	–0.1402	–1.116	6.846[b]
Fixed factors			
Operator labor	–0.2201	0.434	NA
Unpaid labor	–0.8811	–2.526[a]	NA
Herd size	0.2797	0.923	NA

a. Statistically different from H_o: at the 5 percent level of significance.
b. Statistically different from H_o: at the 1 percent level of significance.
NA Not applicable.

maximizing levels. Statistical inference from the OLS results places expenditures on these inputs at output maximizing levels; however, the RCR results show these expenditures fall short of output maximizing levels. The RCR results in general show farmers do much better in allocating input expenditures than we would infer from the fixed coefficients (OLS) approach. This is because the RCR model estimates parameters for each farm.

We also investigated the variability of individual farm coefficients. In particular, we were interested in the relationship between predicted individual coefficients from the RCR and profitability of farms. We divided farms into two groups depending on whether profits were negative or positive. We expect input allocations of profitable farms to be closer to the conditions of profit maximization. If this is true, individual coefficients of profitable farms will be closer to zero than the coefficients of unprofitable farms. Table 4 shows this to be true for ten of the eleven input categories. Analysis of variance showed that means of individual coefficients for the positive-profit group were statistically different from means for the negative-profit group for five input categories. Four of the five categories, land, purchased feeds, hired labor, and marketing, were statistically closer to zero for the group of farms with positive profits. Only the category livestock supplies showed contradictory results.

We further investigated relationships between individual coefficients and profitability using simple regressions of individual coefficients on farm profit levels. In

Table 4.
Comparison of Predicted Parameters by Farm Profitability

	Means of Individual Predicted Parameters		
	All Farms (N = 33)	Profits < 0 (N = 17)	Profits > 0 (N = 16)
Inputs			
Fuels and utilities	−0.1321	−0.1346	−0.1300
Crop production	−0.0001	−0.0016	0.0003
Business and office	0.2705	0.2893	0.2647
Land	−0.2819	−0.8252[a]	0.1127[a]
Purchased feeds	−0.1561	−0.3358[a]	−0.0744[a]
Hired labor	−0.2981	−0.3317[a]	−0.2630[a]
Livestock purchases	−1.8416	−1.8883	−1.8329
Livestock supplies	1.4113	1.3968[a]	1.5017[a]
Marketing	−0.4411	−0.6088[a]	−0.3335[a]
Machinery repairs and supplies	−0.3377	−0.3391	−0.3357
Depreciation	−0.1402	−0.1888	−0.1268

a. Means of the two profit groups were statistically different at the 5% level of significance.

five of eleven cases, coefficients became closer to zero as farm profits increased. The regression results supported the analysis of variance results. Additionally, we found a significant relationship between the individual coefficients for fuels and utilities and profits. We again found the opposite relationship for livestock supplies. Thus, profitable farmers more closely approximate the profit maximizing rule than do their unprofitable counterparts. While this statement may seem tautological, it is a valid reason for the observed variability in individual farm profitability. Profitable dairy farmers in Massachusetts are those who are more adept at allocating input expenditures according to conditions of profit maximization. Thus, farmers with lower levels of profit per cow would do well to reconsider their input allocation decisions.

Summary and Conclusions

Results from both OLS regression and RCR analyses show that farmers do not follow a consistent decision-making rule when allocating input expenditures. Notably, hired labor and machinery repairs and supplies are two input categories where expenditures are in excess of profit maximizing levels. Results from both the OLS model and the RCR showed that on average Massachusetts dairy farmers over-spend on these two inputs. Our results also show that farmers spend less on livestock supplies than is optimal. This is important since expenditures on livestock supplies are for veterinary services and breeding. Increased expenditures on herd health and breeding may provide dairy farmers with substantial rates of return. These results are important as the dairy industry moves toward a period of decreased output price following strong prices in 1990.

We used the results from the RCR to compare expenditure allocation by profitable farms versus unprofitable farms. Profitable farmers are closer to profit maximizing levels of several inputs than their unprofitable counterparts. Hired labor and purchased feeds are two important inputs where profitable farms better allocate their expenditures. These two inputs capture a combined 47.5 percent of total expenditures. However, profitable farmers do no better in allocating expenditures to capital items. There were no significant differences between the allocations of expenditures to machinery repairs and supplies and depreciation for the two groups. We found profitable farmers to more efficiently allocate expenditures to two other input categories, land and marketing expenditures.

We applied our analysis to a small sample of Massachusetts dairy farms. However, the analysis shows promise in directing the establishment of industry standards or *benchmarks* for dairy farm budget analysis. Establishing *benchmarks* from survey data can provide misleading information to producers. The results here suggest that on average several farm inputs are used in excess of levels necessary to maximize profits. We can further use results from the RCR to identify efficiency of allocations by individual farm operators. For instance, researchers can use expenditure levels for individual farms that more closely approximate optimal allocations to establish *benchmarks.* We can also identify farmers whose input expenditures are not consistent with profit maximization. Researchers can use the model as an important planning tool.

Notes

1. Bravo-Ureta and Reiger are an exception. However, they use state-level prices, which are valid only if very strict aggregation conditions are met.
2. The model used here is a simplified version of the Swamy and Tinsley model since we consider only a single time period.
3. The possibility of heteroskedasticity was not of concern since the Swamy and Tinsley estimators correct for such problems.

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Appendix

Parameter estimates of the model are interpreted as follows:

$$\beta_j = \frac{\partial \Pi_i}{\partial E_{ij}} = \frac{d\Pi_i}{dE_{ij}} \bigg| \; dE_{ik} = 0 \;\; k \neq j \tag{A.1}$$

If all prices are fixed across farms, the variations in Π_i and E_{ij} are due to differences in input levels. Considering the partial differential further, the implications for firm behavior become apparent:

$$\frac{\partial \Pi_i}{\partial E_{ij}} = \frac{d\,[\bar{p}Q_i - \sum_j \bar{r}_j X_{ij}]}{d[r_j X_{ij}]} \bigg| \; dE_{ik} = 0 \;\; k \neq j \tag{A.2}$$

and:

$$\frac{\partial \Pi_i}{\partial E_{ij}} = \left(\frac{\bar{p}}{\bar{r}_j} \; \frac{\partial Q_i}{\partial X_{ij}}\right) - 1. \tag{A.3}$$

If firms maximize profits (as we typically *assume* they do), then the parameter estimates for all input categories should be zero by the first order conditions:

$$\bar{p}\frac{\partial Q_i}{\partial X_{ij}} = \bar{r}_j. \tag{A.4}$$

Alternatively, if the firm maximizes output, all parameter estimates will equal minus 1 since marginal products will be zero.