Analyzing the Sources of Technical Efficiency among Heterogeneous Dairy Farms: A Quantile Regression Approach

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Abstract. An unbalanced panel data including 1,151 farm observations from 2004 to 2008 was used to analyze the determinants of technical efficiency (TE) for dairy farms in the State of Wisconsin. To account for farm heterogeneity in our analysis we implemented a two-step framework using a stochastic production frontier and a quantile regression analysis. Our results show that the determinants of TE affect in very specific ways farmers with different levels of TE. This outcome is of significant importance from an empirical point of view. Farmers could use this knowledge to find alternatives to improve their specific level of performance. Additionally, policy makers could use this information to improve the effectiveness of their policies by targeting specific agricultural services and aid to group of farmers with similar levels of TE.

Key Words : technical efficiency, dairy farms

Introduction

The US dairy industry is facing several economic challenges and opportunities at both the international and domestic levels. At the international level, the Uruguay Round of the General Agreements on Tariffs and Trade imposes limits on the use of subsidized exports and also transforms dairy import quotas into tariffs. On the other hand, increasing demand for dairy products from developing as well as from developed countries offers viable opportunities for this industry (Murova and Chidmi, 2009). At the domestic level, dairy markets are been shaped by several factors including: 1) structural changes in the dairy industry (e.g., large size and smaller number of dairy farms, consolidation of dairy cooperatives, and consolidation of retailers); 2) the dynamics of consumer demands; and 3) changing policies. Additionally, dairy farms in traditional states must compete against an ever growing supply from emerging dairy states (Cabrera et al., 2008). Under these circumstances, several studies have suggested that dairy farms in traditional production areas must improve their levels of technical efficiency (TE) if they are to survive in this complex and evolving market (Tauer, 2001; Alvarez et al., 2008; Cabrera et al., 2010).

The accurate analysis of the determinant of TE is critical to the dairy farmers as well as to policy makers. For the farmers, understanding how different factors affect their TE is a helpful tool for improving the performance and profitability of their dairy farms. From the policy makers' viewpoint, knowing the distribution of TE across dairy farms will help to draft specific and well defined dairy policies, which would increase TE and the competitiveness of this industry.

Consequently, the objective of this study is to evaluate the determinants of TE among dairy farms in the State of Wisconsin. Special attention is given in this work to account for the potential effect of farm heterogeneity when analyzing the sources of farm inefficiency. Previous studies addressing the issue of farm heterogeneity have either used 'expert-knowledge' (e.g., Newman and Matthews, 2006; Tauer, 2005; Bravo-Ureta, 1986) or statistical techniques (e.g., Alvarez and del Corral, 2010; Alvarez et al., 2008) to divide the sample using some specific technological characteristics (i.e., herd breed, milking systems, specialization) and then estimate independent production frontiers for groups of farmers with different technologies. However, Cabrera et al. (2010) show that for a cross-section of the sample used in this study, technological differences (i.e., milking systems, housing, and the use of pastures) have no significant impact on the farm level of efficiency. Similar outcomes can be found in Tauer (1993), Hallan and Machado (1996), and Bewley et al. (2001). Thus, in this study we propose an alternative framework to study the sources of farm inefficiency while controlling for farm heterogeneity. Specifically, we implement a two-step framework, in which the TE scores are computed using the stochastic production frontier (SPF) method and then determinants of inefficiency are analyzed using a quantile regression. This framework will allow us to assess the specific impact of different farm's managerial characteristics on the TE of alternative groups of farms clustered on their own level of efficiency. Our running hypothesis is that impact of different factors on the dairy farm TE will vary depending on how far each farm is from the production frontier.

It is important to indicate that previous studies using a two-step approach based on Ordinary Least Square and/or dichotomous (Probit and Tobit) regressions have been criticized due to inconsistencies in the distribution of the TE score and the distribution assumed in the second step. In this study, we control for this issue by using quantile regression that offers the flexibility for modeling data with heterogeneous conditional distributions and makes no distributional assumption about the error term in the model (Chen, 2005; Koenker and Hallock, 2001).

This paper also adds to the literature by analyzing the impact on TE of some variables which have not received much attention in the past such as government payments, alternative sources of farm income and farm financial health.

Materials and Methods

Model

We implement a two-step approach to analyze the level and determinants of TE among a sample of dairy farms in Wisconsin. In the first step, we estimate an SPF following the framework proposed by Aigner et al. (1977). The SPF method is based on an econometric (i.e., parametric) specification of a production frontier. Using a Cobb-Douglas production function and panel data, this method can be presented as:

$$\ln y_{it} = \sum_{i=0}^{m} \beta_i \ln x_{ijt} - \varepsilon_{it} \qquad [1]$$

where *y* represents output, *x* is the amount of inputs, *β*s are the unknown parameters, and ε is the error-term. The subscripts *i*, *j*, and *t* denote the farm, inputs and time, respectively. The error-term is farm-specific and is composed of two independent components, ε_{it} = v_{it} - u_{it}. The first element, *v*, is a random variable reflecting noise and other stochastic shocks which is assumed to be an independent and identically distributed normal random variable with 0 mean and constant variance, iid [N~(0,σ_v^2)]. The second component, *u*, captures technical inefficiency (TI) relative to the stochastic frontier. The inefficiency term *u* is non-negative and it is assumed to follow a half-normal distribution (Kumbhakar and Lovell, 2000).

An index for TE can be defined as the ratio of the observed output (*y*) and maximum feasible output (*y**):

$$\mathrm{TE}_{\mathrm{i}} = \frac{y_i}{y_i\,*} = \frac{f(x_{ij};\beta)\cdot\exp(v_i - u_i)}{f(x_{ij};\beta)\cdot\exp(v_i)} = \exp(-u_i);\ \mathrm{TI} = 1 - \mathrm{TE} \qquad [2]$$

In the second step, we use quantile regression to regress TI on a set of variables, *z*, that influence the inefficiency term u_i: $E(TE \mid Z = z) = z'\theta$. The conditional quantile parameters can be estimated by solving $\hat{\theta} = \arg\min \sum_{i=1}^{n} \rho_\tau (TI_i - z'_i\,\theta)$, with $\rho_\tau = \tau$ if the observation belongs to the τ^{th} quantile and $\rho_\tau = 1 - \tau$ if not.

Data and empirical model

The data used in this study consisted of detailed farm-level information for dairy farms participating in the Agriculture Financial Advisor (AgFA) program managed by the Center for Dairy Profitability at the University of Wisconsin-Madison. The empirical sample included 1,151 Wisconsin dairy farm observations and the collected information covered the period from 2004 to 2008. The dairy farms in the sample were highly specialized with most of their output coming from dairy sales. It is important to indicate that Cabrera et al. (2010) used a cross section of this data set (2007 agricultural year) to analyze the determinants of TE using a one-step SPF framework following *Caudill et al.* (*1995)*.

As indicated, the first-step in the empirical analysis is based on the estimation of a Cobb-Douglas production function. The dependent variable is the total milk production sold measured in kg. Following Cabrera et al. (2010), we included 6 inputs: cow, defined as the number of adult cows (all cows after first calving) in the herd and measures the livestock capital; feed, defined as the total cost of purchased feedstuffs in US \$; capital, defined as the depreciation of buildings and land, corresponding to 5% of the value of land used by the farm; crop, defined as the total expenses related to crop production measured in US \$ (including chemicals, fertilizers, lime, seeds and plant purchases, machinery depreciation, machinery hire expenses, machinery repair, fuel and oil expenses); and labor, defined as the total labor including family and hired labor measured in US \$. In addition, a dummy variable for the year 2005 (drought) was included to account for a severe drought that affected the production of grass and other agricultural products. Because our sample is a highly unbalanced (i.e., farms vary between time period) it is inefficient to implement any panel data techniques (fixed and random effects) in this study. To alleviate the problem, we included in the regression a time trend variable (t) to account for any technical change during this period.

In the second-step, TI was regressed on several managerial characteristics of the dairy farms. The inefficiency model included: a set of milking system dummy variables, including flat barn and pit parlor (pipeline was the omitted variable); milking frequency, a dummy variable equals 1 for the farms with a milking frequency equal to 2 (0 equals more than 2 times); bST, the percent of cows under bovine somatotropin treatment; family labor, the ratio of family labor over total labor; and housing, a dummy variable equals 1 for farms that use free stall housing. During the last years, several studies have shown the importance of intensification of production on the efficiency of dairy farms (e.g., Ledgard et al, 2004; Alvarez et al. 2009; Cabrera et al., 2010); thus, to assess the impact of intensification on efficiency, we included the following variables: feed/cow, defined as the ratio of purchased feedstuffs to the number of cows; TMR, a dummy variable equal to 1 for the farm that used the Total Mixed Ration feeding system; and, pasture, a dummy variable equal to 1 for farms that used pasture feeding systems. Additionally, we also analyzed the effect of other sources of income on TE by including the variables government payments, non-farm income, and the revenue from calves and crops sold, all measured in US $. Finally, to study the effect of the dairy farm's financial health on efficiency, we included the family savings, the investment per cow, and a ratio measuring the debt per cow. Table 1 presents descriptive statistics for all the variables included in the analysis.

Results and Discussion

Frontier analysis

Table 2 presents the maximum likelihood estimates of the Cobb-Douglas production frontier model from the first-step. All estimated parameters are positive and, with the exception of capital, they are all statistically significant. Given that all input variables and the output are in logarithmic form, the parameter estimates can be interpreted as partial production elasticities. The empirical results indicate that the variable that contributes the most to farm production is cows. Specifically, a 10% increase in the number of cows in the herd translates in an increase in milk production sold of 7.78%. The next highest elasticity is for feed (1.34%), followed by crops (0.71%), and labor (0.45%).

The time trend (*t*) is negative and statistically significant indicating a decreasing rate in production levels during the studied period. This result agrees with the findings presented by Ball (2009) who shows that during the last decade traditional dairy states in the US, including Wisconsin, have decreased their level of production, while states in the American West and Southwest have displayed significant improvements. In addition, the parameter for the variable *drought* is also negative and significant suggesting that the adverse climatic condition of 2005 negatively affected the farms' average level of production. This outcome confirms the idea stated by Demir and Mahmud (2002) regarding the importance of controlling for climatic and environmental conditions when studying TE in agriculture.

The empirical results also suggest the presence of constant returns to scale (CRS). Specifically, the scale elasticity (i.e., the sum of all output elasticities) is equal to 1.022. This outcome is confirmed by a likelihood ratio test that failed to reject of the hypothesis $H_0 : \sum \beta_i = 1$. Kompas and Chu (2006) indicates that CRS implies that, for the studied sample, productivity depends on improvements in technology and efficiency, and not necessarily on the size of the farm. The implication of CRS is that there is no scale effect in the size of the farm: the output produced and the farm size will be proportional. Therefore an improvement in productivity (not production) can only come from improvement in technology and efficiency and not from the farm size. However, the size will affect the production (not the productivity). Given constant returns to scale, the dairy farms in our sample are scale efficient.

The distribution of the TE estimates is presented in Figure 1. The results indicate that, on average, the studied dairy farms have a TE exceeding 90%, with a standard deviation of 0.056. It is important to indicate that average level of efficiency obtained here is slightly higher than that reported by previous studies. Bravo-Ureta et al. (2007) show, in their meta-regression analysis of TE in agriculture, an 84% average TE for stochastic frontier studies focusing on dairy farms in developed countries. However, higher levels of TE to those found in this study can be found in Alvarez and del Corral (2010), Abdulai and Tietje (2007), Richards and Jeffrey (2000) for dairy farms in Spain, Germany, and Canada, respectively.

Inefficiency analysis

In the second step, TI is regressed on different farm's managerial characteristics using the quantile regression technique.

Quantile regression models the relationship between inefficiency and the farm's characteristics using the conditional quantile, allowing us to evaluate the specific impact of these characteristics on different groups of farms clustered on their level of efficiency. The results of the quantile regression are presented in Table 3. Given the inverse relationship between TI and TE (see eq. [2]), and because TI is the dependent variable in this analysis, a negative effect on TI has a positive impact on TE.

The empirical results show that *TMR* estimate is positive but not statistically different from zero for the 10th, 20th, and 30th quantiles. In other words, TMR does not significantly affect the efficiency of the most efficient dairy farms. In contrast, for less efficient ones (60th to 90th TI quantiles), the parameter estimate is negative and statistically significant; which shows improvements in TE by adopting the TMR system. Similarly, the ratio of *feed per cow* has a positive and statistically significant impact on TE for the less efficient dairy farms and a positive but not significant impact for most efficient ones. These results imply that, in general, an increase in the intensification of a farm leads to improvements in TE, especially among less efficient farms, which is consistent with the literature (e.g., Cabrera et al., 2010; Kompas and Chu, 2006).

The use of bST for lactating cows has the effect to increase TE as revealed by the negative parameter estimate of this variable. This is not surprising since Bauman et al. (1999) show that the use of bST increases milk production and feed efficiency. It is worth noticing that this result does not depend on the type of the dairy farm as the parameter estimate is positive for all inefficiency quantiles.

In contrast, as milking frequency increases, TE decreases for all quantiles as indicated by the positive and statistically significant parameter estimate of this variable. This result contradicts some previous studies (e.g., Erdman and Varner, 1994) who report 3.5 to 4.9 kg/day increase in milk production when cows are milked 3 and 4 times daily compared to only 2 times milking in a day. However, Cabrera et al. (2010) argue that additional milk frequencies imply additional labor and additional feed intake which might affect the level of efficiency of the farm depending on the market conditions and farm characteristics.

In relation to the milking system used in the farm, the results show that relative to pipeline parlor (the omitted variable), the use of flat barn and pit parlor increases dairy farms' inefficiency as indicated by positive parameter estimates of these variables. For instance, the effect of flat barn on inefficiency increases as we move from the most TE dairy farms to the less efficient ones. Table 3 shows that the negative effect of flat barn on technical efficiency is more than 345 fold for the 10th TE percentile than for the 80th TE percentile. Similarly, the effect of pit parlor is accentuated as dairy farms become less efficient. However, the parameter estimates for both milking systems are not statistically significant for the upper TE quantiles. In terms of the housing type, our results indicate that the type of housing has no significant impact on TE, which is consistent with consistent with Bewley et al. (2001), Hallan and Machado (1996), and Cabrera et al. (2010).

One of the goals of this study was to assess the effect of the government payments on TE by type of dairy farms. Overall, government payments have a positive and statistically significant effect on TE for farms in the lower TE quantiles. However, these payments have no statistically significant effect on the TE of dairy farms that are already close to the frontier, the 90th quantile. As we move far from the frontier, the effect of government payments on TE increases. In fact, this effect on TI is -0.007 for more from government payments than more efficient dairy farms the 10th TI quantile, while it is -0.061 for the upper 90th TI quantile. In

Table 1. Descriptive statistics for Wisconsin dairy farms (N=1,151, yrs. 2004-2008)

Variable (unit)	Mean	Std Dev	Minimum	Maximum
Milk (kg)	3,081,791	4,212,449	360,807	47,972,970
Cows (n)	140	176	23	1,844
Feed ($)	116,023	184,823	2,760	1,867,926
Capital ($)	90,905	97,070	6,279	1,626,164
Crop ($)	139,325	151,217	3,733	1,585,638
Labor ($)	57,188	106,025	161	1,227,002
TMR (dummy)[1]	0.53	0.50	0	1
Pature (dummy)[2]	0.16	0.37	0	1
Milking system (dummy)[3]				
Flat barn	0.09	0.28	0	1
Pit parlor	0.26	0.44	0	1
Milking frequency (dummy)[4]	0.91	0.29	0	1
bST (%)	14.62	25.07	0	100
Family labor (%)	58.96	44.09	0	100
Feed/cow (ratio)	705.50	325.98	52.77	2,026.65
Housing (dummy)[5]	0.39	0.49	0	1
Government payments ($)	0.16	0.16	0.00	1.06
Nonfarm income ($)	0.14	0.27	0.00	3.12
Calves sold ($)	0.12	0.26	0.00	3.90
Crop sold ($)	0.18	0.38	0.00	3.19
Family savings ($)	0.49	0.50	-2.02	3.26
Investment/cow (ratio)	0.12	0.05	0.04	0.38
Debt/cow (ratio)	0.03	0.02	0.00	0.11

[1]Use of TMR = 1; [2]Use of pasture = 1; [3]Pipeline is the omitted variable; [4]Two times daily milking frequency = 1; [5]Free stall housing = 1

Table 2. Production frontier estimates (N=1,151, yrs. 2004-2008)

Variables[1]	Coefficient	Std. Dev.	t-value
Constant	8.489***	0.099	85.22
Cow (n)	0.778***	0.017	46.23
Feed ($)	0.134***	0.008	17.56
Capital ($)	-0.006	0.010	-0.60
Crop ($)	0.071***	0.009	7.44
Labor ($)	0.045***	0.004	11.72
Time Trend	-0.019***	0.003	-6.18
Drought (dummy)	-0.034***	0.010	-3.35
σ_v	0.066***	0.005	12.67
σ_u	0.199***	0.008	2,489.00
Log-likelihood	701.98		
Log-likelihood ratio	0.90	Fail to reject H_0	

*P < 0.10; **P < 0.05; ***P < 0.01. [1]Dependent variable is the total milk production sold measured in kg.

Figure 1. Distribution of Technical Efficiency

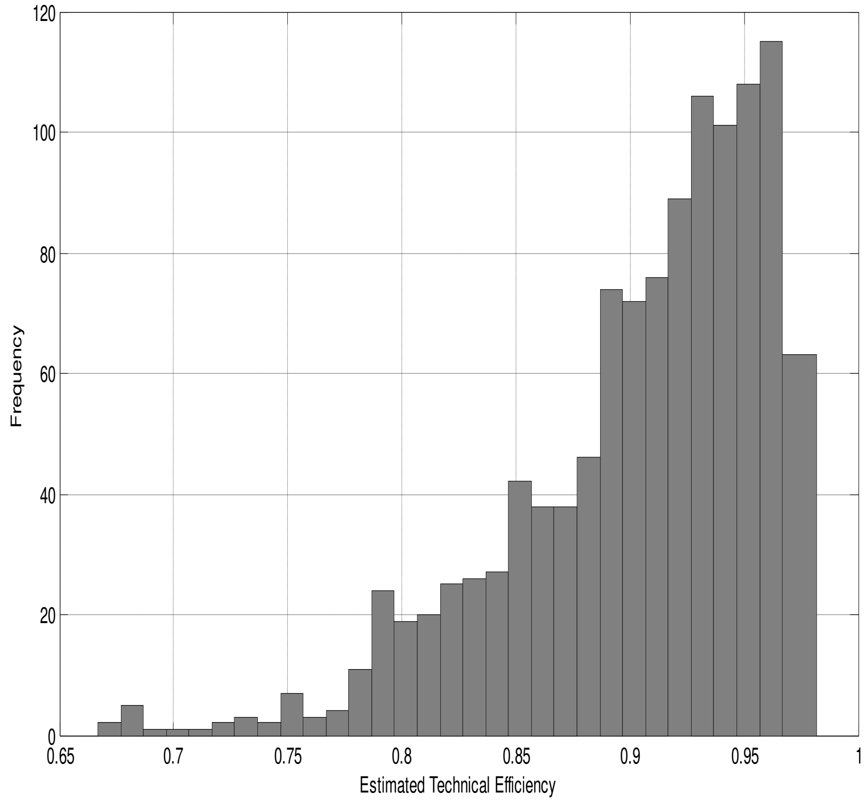

Table 3. Inefficiency analysis (N=1,151)

Variables[1]	Quantiles								
	0.1	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
Constant	0.0410***	0.0496***	0.0550***	0.0680***	0.0752***	0.1063***	0.1321***	0.1824***	0.2533***
TMR Dummy	0.0048	0.0041	0.0033	-0.0029	-0.0055	-0.0088*	-0.0059	-0.0160*	-0.038***
Waste handling	0.0035	0.0110***	0.0118***	0.0113***	0.0178***	0.0199***	0.0251***	0.0355***	0.0408***
Flat barn	-0.0018	0.0001	0.0038	0.0140	0.0173**	0.0256***	0.0272***	0.0358***	0.0345***
Pit parlor	-0.0046	0.0014	0.0095	0.0132*	0.0183***	0.0140*	0.0194**	0.0328***	0.0440***
Milking frequency	0.0047	0.0107***	0.0159***	0.0218***	0.0249***	0.0256***	0.0267***	0.0341***	0.0384***
BST (%)	-0.0003***	-0.0004***	-0.0004***	-0.0005***	-0.0005***	-0.0006***	-0.0007***	-0.0007***	-0.0006***
Feed/cow ratio	0.0000	0.0000***	0.0000	0.0000	-0.0000	-0.000***	-0.000***	-0.000***	-0.000***
Free stall housing dummy	0.0049	0.0075*	0.0076	0.0058	0.0055	0.0021	-0.0035	-0.0062	-0.0158*
Government payments	-0.0075	-0.0091	-0.0082	-0.0027	-0.0002	-0.0128	-0.0180	-0.0320*	-0.061***
Nonfarm income	0.0018	0.0039	0.0168***	0.0278***	0.0374***	0.0420***	0.0486***	0.0464***	0.0496***
Calves sold	0.0204***	0.0209***	0.0234***	0.0282***	0.0301***	0.0312***	0.0338***	0.0405***	0.0468*
Crop sold	0.0201***	0.0252***	0.0313***	0.0368***	0.0435***	0.0510***	0.0485***	0.0620***	0.0630***
Family savings	-0.0070	-0.0118***	-0.0192***	-0.024***	-0.026***	-0.021***	-0.022***	-0.032***	-0.034***
Investment/cow	-0.074***	-0.1162***	-0.1034***	-0.149***	-0.155***	-0.229***	-0.270***	-0.373***	-0.458***
Debt/cow	0.1532***	0.1052***	0.1999***	0.2316***	0.2818***	0.3082***	0.4050***	0.2206*	0.2761*

*P < 0.10; **P < 0.05; ***P < 0.01; [1] Dependent variable is the farm technical inefficiency, u

other words, the effect of government support on the TE of the less efficient farms is more than eight times higher than the effect on most efficient farms. This outcome is very interesting for policy makers: less efficient dairy farms would benefit.

Our results show that nonfarm income has a negative effect on farm efficiency regardless of the TI quantiles. This finding is consistent with the argument that off-farm work negatively affects agricultural production. Bravo-Ureta et al. (2006) explain that off-farm activities reduce the time available for agricultural work and that farmers involved in nonfarm activities are less concerned about improving the productivity and efficiency of their farm. This argument is confirmed by the positive and significant effect of family labor on the farm TE. Similar conclusions can be drawn for the income provided by activities other than dairy farming, such as calves and crops sales. These activities have a negative and statistically significant impact on TE. Moreover, the effect is more accentuated as we move from upper TE farms to lower ones.

In addition, the financial health of the dairy farms plays an important role in TE. The results of this study indicate that as the investment per cow increases, TE also increases for all quantiles. Moreover, this increase is more accentuated for lower levels of technical efficiency. In contrast, as the debt per cow increases, TE decreases, especially for lower level quantiles. Finally, the level of family savings has also a positive effect on TE, with an accentuated effect for lower level quantiles. This is may be due to the fact that families with higher savings are able to invest more on their farms and contract less debt than the ones with lower savings.

Conclusions

This study analyses the determinants of TE among a sample of dairy farms in the State of Wisconsin. Our results show that the determinants of TE affect in very specific ways farmers with different levels of TE. This result confirms our hypothesis on the importance of controlling for farm heterogeneity when analyzing the determinants of TE. The results of this study indicate that feeding factors, such as the use of TMR and feed per cow, affect positively TE of dairy farms with lower TE levels; and negatively or they do not have an impact on TE efficiency of farms with higher TE levels. Another interesting finding is that, although all dairy farms would benefit from government payments, government payments contribute more to the increase of TE of dairy farms with lower TE levels than farms with higher TE levels. For example, the effect of the government payments on TE is about eight fold higher for lower TE farms than for the higher TE farms.

The results also show that income either from non-farm activities or activities other than dairy farming have a negative effect on TE efficiency, regardless of the farm type. In addition, the farm's financial health plays an important role in technical efficiency. Technical efficiency increases as family savings and investment per cow increase and decreases as debt per cow increases.

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