Analyzing the Determinants of Technical Efficiency among Traditional Dairy Farms in Wisconsin: A Quantile Regression Approach

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Abstract:

This study analyzes the determinants of TE among traditional dairy farms in the State of Wisconsin taking into account dairy farms' heterogeneity. To do so, we first estimate a production frontier and the level of TE using the SPF framework. Then we analyze the determinants of TI using a quantile regression analysis. The results indicate 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. This issue is also important from an empirical point of view. Policy makers could improve the effectiveness of their work by targeting specific agricultural services and aid designed for farmers with different level of TE.

Keywords: technical efficiency, dairy, quantile regression

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The United States (U.S.) dairy industry is facing several 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 a limit on the use of subsidized exports, and also transforms dairy imports quotas into tariffs. However, increasing demand for dairy products from developing-country consumers offers opportunities for U.S. dairy industry (Murova and Chidmi, 2009). At the domestic level, dairy markets are shaped by several factors including: 1) structural changes in the dairy industry (e.g., size and number of dairy farms, consolidation of dairy cooperatives, and consolidation of retailers); 2) the dynamics of dairy relocation, 3) the dynamics of consumer demands; and 3) changing policies.

To cope with these challenges and exploit these opportunities, traditional dairy farms in the U.S. -especially those in Wisconsin- must be competitive with an ever growing dairy product supply from foreign countries, and emerging western and southwestern states. For instance, in 1975, Wisconsin dairy farms produced 16% of the total national milk production and only 13% in 2003; while for California, these figures were 9% and 21%, respectively (CITEC, 2005). In addition, the U.S. milk production is shifting to new large dairies, especially from emerging states like California. In 2004, farms with less than 200 cows represented 67% of herd in Wisconsin and only 2% in California. In contrast, farms with more than 500 heads represented 86% in California but only 16% in Wisconsin. Under these circumstances, the improvement of technical efficiency (TE) in operating dairy farms in traditional production states has been proposed as a crucial factor for their survival (Tauer, 2001; Cabrera et al., 2009).

Therefore, the objective of this study is to estimate the level of technical inefficiency (TI) among dairy farms in the State of Wisconsin and evaluate the determinants of such inefficiency using a stochastic production frontier (SPF) model. However, unlike previous studies that assume that the determinants of TI behave constantly along all the farms in the sample, we propose a two-step approach to account for potential farm heterogeneity. Specifically, we first estimate a Cobb-Douglas production model and estimate the TI. Then, we use a quantile regression procedure to analyze the impact of alternative production systems, farm size, farmers' income, government payment, and non-family labor, among other variables, on TI. By doing so, our hypothesis is that there will be different impact of these factors on dairy farms TE, depending on how far each farm is from the production frontier.

Traditionally the main concern of efficiency studies in dairy industry was to analyze TE using either a parametric (stochastic frontier analysis) or a non-parametric approach (data envelopment analysis) with cross-sectional data. For example, Cabrera et al. (2009) analyze the extent to which technical efficiency is related to practices and the effect of intensification on the performance of dairy farms in Wisconsin, U.S. Using a SPF, the authors find that TE is positively related to farm intensification, the level of contribution of family labor in the farm activities, the use of total mixed ration feeding system, and the administration of bovine somatotropin (bST) hormone to lactating cows. Similarly, Murova and Chidmi (2009) also use a SPF and a data envelopment analysis augmented with logistic regression to analyze the impact of some federal milk policies on the performance of dairy farms in United States. The authors find that federal milk marketing program has a negative and significant impact on TE.

Another type of analysis uses the stochastic cost frontier to estimate the cost efficiency of dairies in U. S. Tauer and Mishra (2006), for instance, find that the number of hours per day the milking facility is used has an impact on the cost frontier. This latter decreases as the number of hours the milking facility is used increases. However, inefficiency increases with increased hours of milking facility use.

Although the available literature offers useful insights in studying TE in this sector, they generally fail to account for farm heterogeneity issues. In fact, previous studies assume that the determinants of TI are all constant across heterogeneous dairy farms. For instance, Cabrera et al. (2009)

find that the intensification variable, defined as the ratio of feed purchased per cow, has a positive effect on technical efficiency. However, this study is silent regarding the distribution of this effect across different dairy farms.

Accurate analysis of the determinant of TE is critical to the dairy farmers as well as to the public policy makers. For the farmers, understanding the factors that affect TE is a helpful tool in improving efficiency and performance of dairy farms. From the policy makers' viewpoint, knowing the distribution of TE across dairy farms will help draft specific and well defined dairy policies which would increase technical efficiencies and the competitiveness of dairy farms.

To this end, this paper uses a two-step approach to estimate the level of TE in the sample. In the first step, a SPF is estimated. The implied TI is then regressed on factors, such as the farm size, farm income, the ratio of non-family labor to total labor, government payments, and intensification variables. In the second step, we use the quantile regression introduced by Koenker and Bassett (1978). Unlike traditional regression that takes into account the conditional mean function, the quantile regression offers the possibility to examine the effects of regressors on the shape, location, and dispersion of the dependent variable.

Previous studies using a two-step approach have been criticized in the past due to inconsistencies in the distribution of the TI index and the distribution assumed in the second step. In this study, we control for this issue by using quantile regression that offer the flexibility for modeling data with heterogeneous conditional distributions and makes no distributional assumption about the error term in the model (Chen, 2005).

Model

As indicated, in this study we implement a two-step approach to analyze the level and determinants of TE among a sample of traditional 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 generalized production function and panel data, this method can be presented as

$$y_{it} = f(x_{it};\beta) \times exp(\varepsilon_{it}) \tag{1}$$

where y represents output, x is a vector of inputs, β is a vector of unknown parameters and ε is the error-term. The subscripts i , j and t denote the farm, inputs, and time, respectively. For ease of presentation, the subscript t will be dropped in what follows. The error-term is farm-specific and is composed of two independent components, $\varepsilon_{it} = v_{it} - u + it$. The first element, v_{it}, 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, $i.i.d.N\ (0, ?\sigma_{v^2})$. The second component, u_i, captures technical inefficiency (**TI**) relative to the stochastic frontier. The inefficiency term u_i 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^*)

$$TE_i = \frac{y_i}{y_i^*} = \frac{f(x_i;\beta) \times exp(v_i - u_i)}{f(x_i;\beta) \times exp(v_i)} = exp(-u_i) \tag{2}$$

Previous studies have used the one step approach where the production frontier is estimated along with TE or TI. In this paper, we adopt a two-step approach.[1] In the second step, we use quantile regression to regress TI on variables, z, that influence the inefficiency term u_i: $E(TE|Z = z) = z'\theta$. The conditional quantile parameters can be estimated by solving

$$\hat{\theta} = argmin \sum_{i=1}^{n} \rho_\tau(TI_i - z'\theta) \tag{3}$$

with $\rho_\tau = \tau$ if the observation belongs to the τ^{th} quantile, and $\tau^{th} = 1 - \tau$ if not.

[1] Though the two-step approach is known to be biased, it allows in our case to study how technical efficiency is distributed across dairy farms given farm characteristics and government payments, for example.

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 909 dairy farms and the collected information corresponded to the 2004-2007. The dairy farms in the sample were highly specialized with most of their output coming from dairy sales. All the farms were located in the State of Wisconsin which has traditionally been one of the top states in terms of milk production and dairy farming in the US.

The empirical analysis is based on the estimation of a log-log Cobb-Douglas production function. The dependent variable is the natural logarithm of total milk production sold measured in kg. Following Cabrera et al. (2010)[2] we include 6 inputs: cow, defined as the number of adult cows in the herd; feed, defined as the total cost of purchased feedstuffs in US $; capital, defined as the depreciation of buildings and land, and corresponds to 5% of the value of land use by the farm; crop, defined as the total expenses related to crop production measured in US $ (this includes chemicals, fertilizers, lime, seeds and plant purchases, machinery depreciation, machinery hire expenses, machinery repair, fuel and oil expenses); labor, defined as the total labor including family hired labor measured in US $; livestock, which includes breeding expenses, veterinary and medicines, and other livestock expenses in US $.

In the second step, the inefficiency, u, is regressed on the characteristics of the dairy farms. The analysis includes the farm size (z_1), a dummy variable for total mixed ration (z_2), pasture dummy (z_3), two milking system dummies(flat barn, z_1; and pit parlor, z_{42}), milking frequency (z_5), percent of cows under bST regime (z_6), ratio of family labor (z_7), feed per cow ratio (z_8), housing type dummy (z_9), government payments (z_{10}), non-farm income (z_{11}), calves sales (z_{12}), crops sales (z_{13}), family savings (z_{14}), investment per cow (z_{15}), and debt per cow (z_{16}). Table 1 presents descriptive statistics for all the variables included in the analysis.

[2]Cabrera et al. (2010) use the same data for 2007 agricultural year.

Table 1: Summary Statistics and Variable Definitions (N=909, 2004-2007)

Variable	Label	Mean	Std	Min	Max
lq	Log output	14.47	0.84	12.80	17.69
lx_1, z_1	Log # of cows	4.55	0.77	3.14	7.52
lx_2	Log feed	10.96	1.06	7.92	14.44
lx_3	log capital	11.09	0.74	8.74	14.30
lx_4	Log crop	11.39	0.87	8.22	14.28
lx_5	Log labor	9.93	1.45	5.08	14.02
lx_6	Log livestock	9.93	1.26	4.06	13.62
x_7, z_6	bST (%)	14.83	25.13	0.00	100.00
z_2	Total mixed ration dummy	0.53	0.50	0.00	1.00
z_3	Pasture dummy	0.17	0.37	0.00	1.00
z_{41}	Flat barn dummy	0.09	0.28	0.00	1.00
z_{42}	Pit parlor dummy	0.26	0.44	0.00	1.00
z_5	Milking frequency dummy	0.91	0.29	0.00	1.00
z_7	Family labor (%)	59.01	44.19	0.00	100.00
z_8	Feed/cow ratio	683.03	313.24	52.77	2026.65
z_9	Housing type dummy	0.38	0.49	0.00	1.00
z_{10}	Government payments	0.18	0.17	0.00	1.06
z_{11}	Non-farm income	0.14	0.27	0.00	3.12
z_{12}	Calves sales	0.13	0.27	0.00	3.89
z_{13}	Crops sales	0.17	0.35	0.00	3.19
z_{14}	Family savings	0.49	0.49	0.00	3.26
z_{15}	Investment/cow	0.12	0.05	0.04	0.38
z_{16}	Debt/cow	0.03	0.02	0.00	0.11

Results and Discussion

Table 2 presents the maximum likelihood estimates of the production frontier model from the first step. With the exception of capital, all parameter estimates are statistically significant and with the expect sign. Given that all input variables and the output are in logarithmic form, the parameter estimates represent the output elasticities. Using this fact, the results indicate that a 10% increase in the number of cows increases the milk production by 7.24 %, while the same increase in labor would increase production by only 3.55%. Besides the number of cows, feed has the second highest impact on milk production. Hence, an increase of 10% in feed increase milk production by 1.09%.

The Wald test failed to reject the hypothesis that the sum of the output elasticities is one, implying constant returns to scale (CRS). More precisely, the scale elasticity (i.e., the sum of all output elasticities) was 0.996. This suggests that there is no proportional relationship between the size of the farm and the level of output (Kompas and Chu, 2006). We expect therefore inefficiency/efficiency levels to be independent of the number of cows.

As in previous dairy farms studies (see for example, Bauman et al., 1999; Cabrera et al., 2010) the administration of the hormone bST to lactating cows positively affects the milk production. The parameter estimate of this variable is positive and significant at 1% level. Although the hormone has negative effect on animal reproduction (Bauman, 1989), its use for lactating cows increases feed efficiency in the range of 2.7 t0 9.3% and milk production in the range of 8.5 to 17.6%. Our results show that at the mean, a 10% increase in the percentage of cows under bST regime will increase the milk production by 0.4%.

Table 2: Production Frontier Estimates(N=909, 2004-2007)

Parameter	Label	Estimate	Standard Error	t Value
Intercept	Intercept	8.3058	0.1154	72.00
lx_1	# of cows	0.7238	0.0185	39.07
lx_2	Feed	0.1088	0.0091	11.93
lx_3	Capital	-0.0012	0.0112	-0.11
lx_4	Crop	0.0668	0.0103	6.48
lx_5	Labor	0.0355	0.0044	8.00
lx_6	Livestock	0.0629	0.0066	9.60
x_7	bST (%)	0.0007	0.0002	3.84
y_4	Year 2004 dummy	0.0608	0.0121	5.03
y_5	Year 2005 dummy	0.0258	0.0112	2.30
y_6	Year 2006 dummy	0.0600	0.0113	5.31
σ_v	Sigma v	0.0879	0.0049	18.09
σ_u	Sigma u	0.0912	0.0075	12.21
Wald Test	$H_0 : lx_1 + lx_2 + lx_3 + lx_4 + lx_5 + lx_6 = 1$		$Pr > \chi^2 = 0.5872$	

The distribution of the implied technical efficiency estimates is represented in figure 1. The results indicate that on average, dairy farms in Wisconsin have a TE exceeding 0.9537, with a standard deviation of 0.018. This implies that the milk production could be increased by approximately 5% with the use of the same level of inputs. The lowest technical efficiency is 0.8550, while the highest is 0.9780.

In the second step, the TI is recovered from the results of the first step and regressed on different dairy farms characteristics using the quantile regression technique. Quantile regression models the relationship between inefficiency and farms characteristics using the conditional quantile, such as the median or the 90th percentile. This is important especially when the change in TI depends on the quantile. The results of the quantile regression are summarized in Table 3. For comparison reasons we also included the results using OLS regression which assumed that the determinants of TI affects all the farms in a similar way.

Given that TI is the dependant variable, the 10th percentile, for example, represents the lowest 10 percent dairy farms in TI; or equivalently the 90th percentile of TE. The parameter estimate for the number of cows is positive for all the quantiles, but only significant for the 20th, 30th, and 90th quantiles. For farms in these quantiles, this suggests that increasing the size of the herd would negatively affect TE. This is may be due to the fact that these farms have already reached their minimum efficient scale and any increase in size would lead to diseconomies of scale.

The total mixed ration (TMR) dummy variable coefficient estimate is not statistically different from zero for the 10th, 20th, 30th, and 40th quantiles. In another word, TMR does not affect efficiency for the most efficient dairy farms. In contrast, for less efficient dairy farms, the parameter estimate is negative and statistically significant; suggesting an improvement in technical efficiency as total mixed ration is used. This result is consistent with previous studies, in particular Cabrera et al. (2009) who find TMR to affect positively TE.

Table 3: Quantile Regression Results (Dependent variable: technical inefficiency, u)

Variable / Quantiles	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	OLS
Intercept	0.0178***	0.0199***	0.0259***	0.0319***	0.0344***	0.0369***	0.0450***	0.0515***	0.0725***	0.0512***
# of cows	0.0016	0.0026**	0.0020**	0.0008	0.0004	0.0012	0.0015	0.002	0.0037*	0.0001
TMR dummy	0.0006	-0.0001	0.0006	-0.0005	-0.0013	-0.0027*	-0.0029*	-0.0065***	-0.0137***	-0.0046***
Pasture dummy	0.0027**	0.0035***	0.0045***	0.0056***	0.0065***	0.0058***	0.0069**	0.0096***	0.0161***	0.0067***
Flat barn dummy	0.002	0.0018	0.0047**	0.0044	0.0055**	0.0066**	0.0111***	0.0122***	0.0128***	0.0077***
Pit parlor dummy	0.0007	0.0004	0.002	0.0039*	0.0035*	0.0045***	0.0062**	0.0072***	0.0098***	0.0057**
Milking frequency	0.0049***	0.0065***	0.0057***	0.0064***	0.0067***	0.0081***	0.0074***	0.0072**	0.0063*	0.0068***
bST (%)	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***
Family labor	0.0001*	0.0001*	0.0001	0.0001**	0.0001***	0.0001***	0.0001***	0.0001***	0.0001	0.0001***
Feed/cow	0.0001*	0.0001	-0.0001	-0.0001	-0.0001*	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***
Housing type dummy	0.0003	-0.0001	-0.0018	-0.0016	-0.0001	-0.0029	-0.0039*	-0.0041*	-0.0079**	-0.0021
Gov. payments	-0.0009	-0.0027	-0.0061**	-0.0032	-0.0061*	-0.0075*	-0.0121***	-0.0126***	-0.0273***	-0.0132**
Nonfarm income	0.0002	0.0019	0.0034	0.0068**	0.0102***	0.0145***	0.0151***	0.0142***	0.0234***	0.0094***
Calves sold	0.0041***	0.0058***	0.0061***	0.0063***	0.0079***	0.0080***	0.0108***	0.0110***	0.0190***	0.0105***
Crops sold	0.0057***	0.0080***	0.0095***	0.0102***	0.0094***	0.0091***	0.0122***	0.0145***	0.0205***	0.0117***
Family savings	-0.0039***	-0.0055***	-0.0058***	-0.0073***	-0.0067***	-0.0062***	-0.0087***	-0.0091***	-0.0085***	-0.0074***
Investment/cow	-0.0114	-0.0312***	-0.0271**	-0.019	-0.0081	-0.0241**	-0.0311*	-0.0471**	-0.0944***	-0.0552***
Debt/cow	0.0252	0.0459***	0.0691***	0.0819***	0.0679***	0.0642**	0.0497	0.0848**	0.0878	0.0723**

$*: P < 0.10; **: P < 0.05; ***: P < 0.01$

For the ratio of feed per cow, the empirical results indicate that this ratio has a negative impact on technical efficiency for top 20% efficient dairy farms but a positive impact for lower efficient dairy farms. This result is partially consistent with previous findings (e.g. Cabrera et al., 2010; Alvarez et al. (2008); Kompas and Chu, 2006); however, their models does not take into account the dairy farms heterogeneity. In addition, the use of pasture has a negative effect on TE as the parameter estimate of this variable in the inefficiency regression is positive and statistically significant. According to Bargo et al. (2002), pasture systems result in lower milk yields and decreased efficiency.

The use of bST for lactating cows has the effect to increase TE as indicated by the negative and statically significant parameter estimate of this variable. This is not a surprising result as Bauman et al. (1999) suggest that the use of bST increases milk production and feed efficiency. This result does not depend on the type of the dairy farm as the parameter estimate is statistically significant for all inefficiency quantiles. In contrast, as milking frequency increases, technical inefficiency increases 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. However, Cabrera et al. (2010) argue that additional milk frequencies imply additional labor and additional feed intake that might result in more or less efficiency depending on the market conditions and farm characteristics.

In relation with milking, the results show that relative to pipeline parlor, the use of flat barn and pit parlor increases dairy farms inefficiency as indicated by positive parameter estimates of these variables. For flat barn, the effect on inefficiency increases as we move from the most TE dairy farms to the less ones. Figure 3 shows that the negative effect of flat barn on technical efficiency is more than six fold for the 10th TE percentile than for the 90th TE percentile. Similarly, the effect of pit parlor is accentuated as dairy farms become less efficient. However, the parameter estimates for both these milking systems is not statistically significant for the upper TE quantiles (Figure 4).

In terms of housing type, our results indicate that the type of housing has no significant impact on TE for upper TE quantiles, which is consistent with Cabrera et al. (2010). However, for lower TE quantiles, our results show that free stall housing increases TE as we move to less efficient dairy farms. For example, the effect of this variable on technical inefficiency is -0.0039 for the 70th TI percentile and -0.0079 for the 90th TI percentile, or approximately the double. In Figure 5, we can see that if we ignore farm heterogeneity, the obtained estimate are only valid for farms in the quantiles between 30 and 60. As we move farther, the quantile results are different from the mean regression (OLS).

One of the additions of this study is to assess the effect of the government payments on TE by type of dairy farms. Overall, government payments have a positive and significant effect on TE as one would expect. However, these payments have no statistically significant effect on TE of dairy farms that are already close to the frontier. As we move far from the frontier, the effect of government payments on TE increases as indicated by Figure 5. In fact, this effect on TI is -0.0061 for the median dairy farm, while it is -0.0273 for the upper 90th TI quantile. In other words, the effect of government payments on TE for less efficient farms is four times higher than the effect on median farms. This is a very interesting result for policy makers: less efficient dairy farms would benefit more from government payments than more efficient dairy farms.

Our results show that off-farm income has a negative effect on TE regardless of the TE quantiles. This finding is consistent with the argument that off-farm income negatively affects agricultural production, in general, because it reduces the time available for agricultural work and because these farmers may be less concerned about improving their productivity and efficiency due to their orientation towards off-farm employment (Bravo-Ureta et al., 2006). However, as shown by Table 3 and Figure 6, this effect is not statistically significant for upper TE quantiles. In addition, the magnitude of this effect increases as we move from more efficient dairy farms to less efficient 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 level 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.

Conclusion

This study analyzes the determinants of TE among traditional dairy farms in the State of Wisconsin. Unlike previous studies we assume the presence of farm's heterogeneity; thus, the determinants of TI may behave differently along the sample. To do so, we first estimate a production frontier and the level of TE using the SPF framework. Then we analyze the determinants of TI using a quantile regression analysis.

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. This issue is also important from an empirical point of view. Policy makers could improve the effectiveness of their work by targeting specific agricultural services and aid designed for farmers with different level of TE.

Specifically, the results of this study show that government payments have a positive and significant effect on TE as one would expect. However, these payments have no statistically significant effect on TE of dairy farms that are already close to the frontier. As we move far from the frontier, the effect of government payments on TE increases. This is a very interesting result for policy makers: less efficient dairy farms would benefit more from government payments than more efficient dairy farms. In addition, the results show that off-farm income has a negative effect on TE regardless of the TE quantiles; however, this effect is not statistically significant for upper TE quantiles and its magnitude increases as we move from more efficient dairy farms to less efficient ones.

Finally, the financial health of the dairy farms seems to play an important role in TE. Hence, as the investment per cow increases, TE also increases for all quantiles. Moreover, this increase is more accentuated for lower level of technical efficiency. In contrast, as the debt per cow increases, TE decreases, especially for lower level quantiles. Moreover, the level of family savings, has also a positive effect on TE , with an accentuated effect for lower level quantiles.

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Figure 1: Frequency Distribution of Technical Efficiency

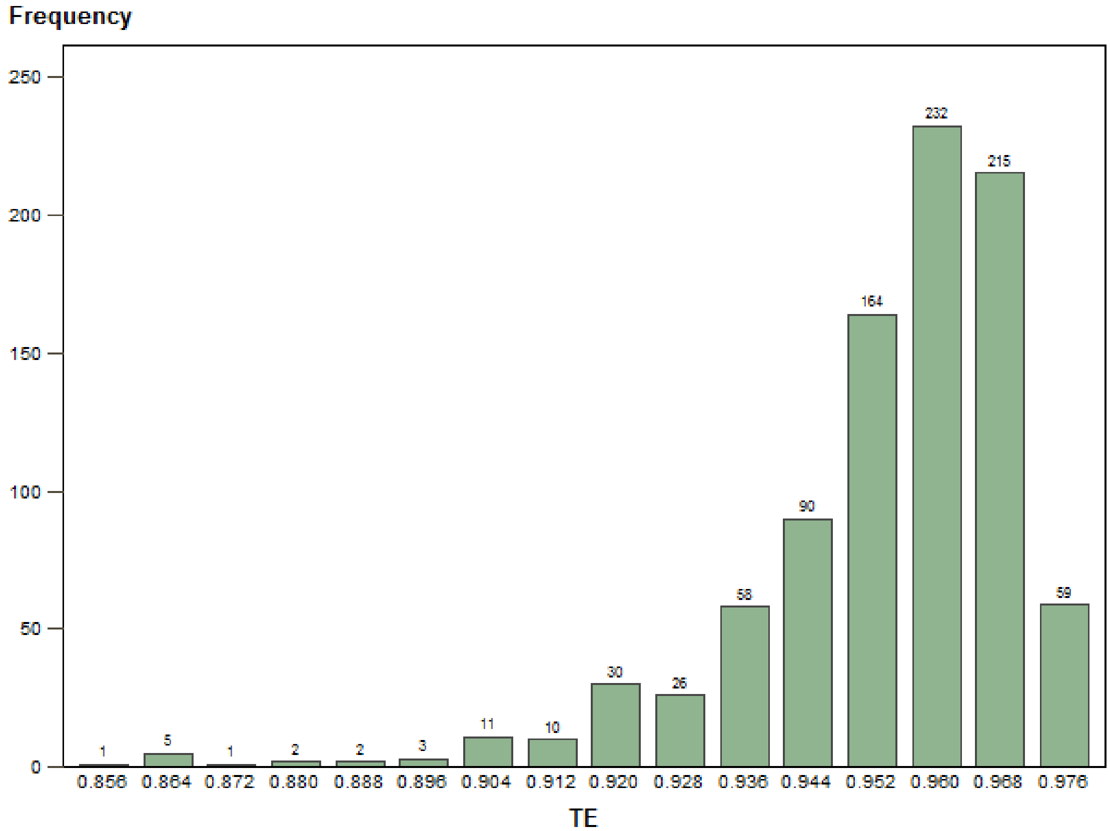

Figure 2: Estimated Parameter for Flat Barn Dummy Variable by Quantile for Inefficiency *u*

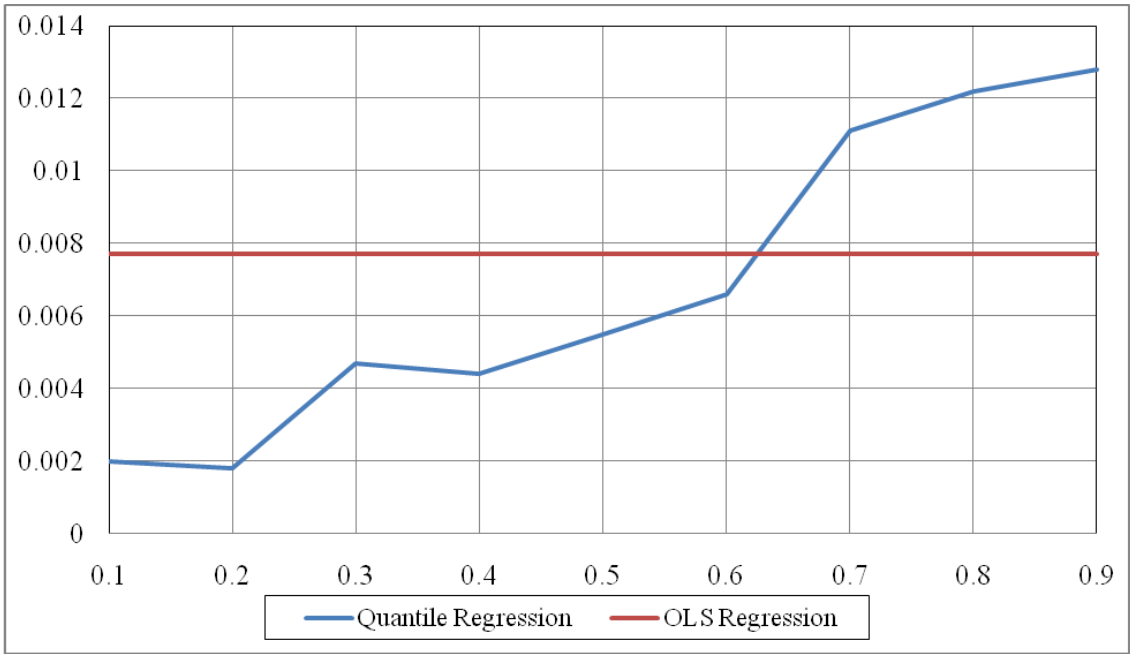

Figure 3: Estimated Parameter for Pit Parlor Dummy Variable by Quantile for Inefficiency *u*

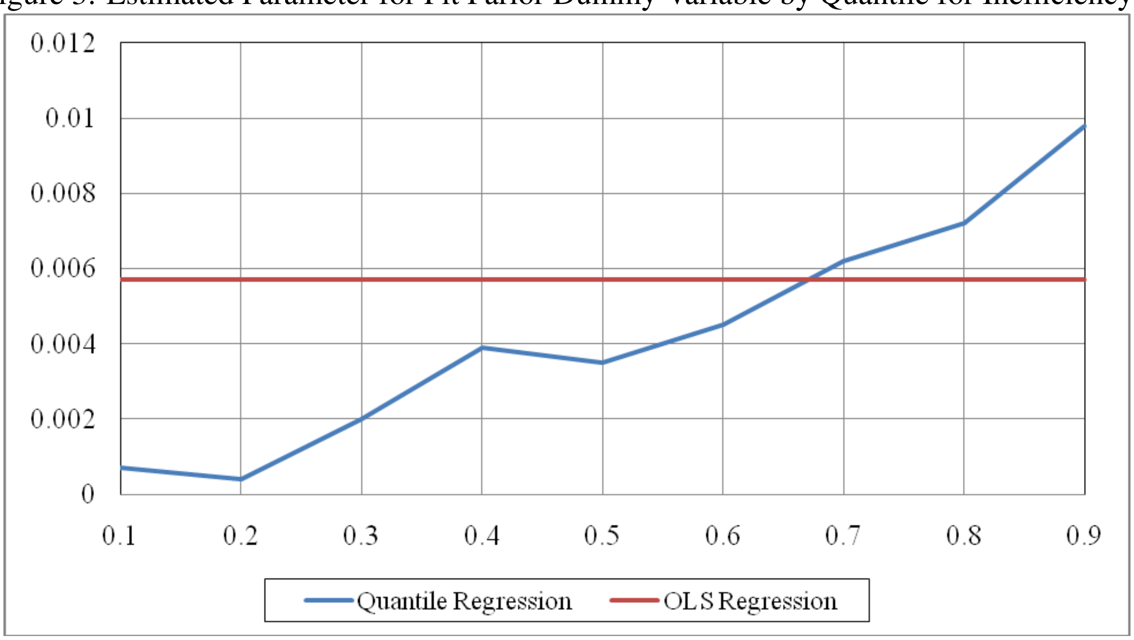

Figure 4: Estimated Parameter for Housing Type Dummy Variable by Quantile for Inefficiency u

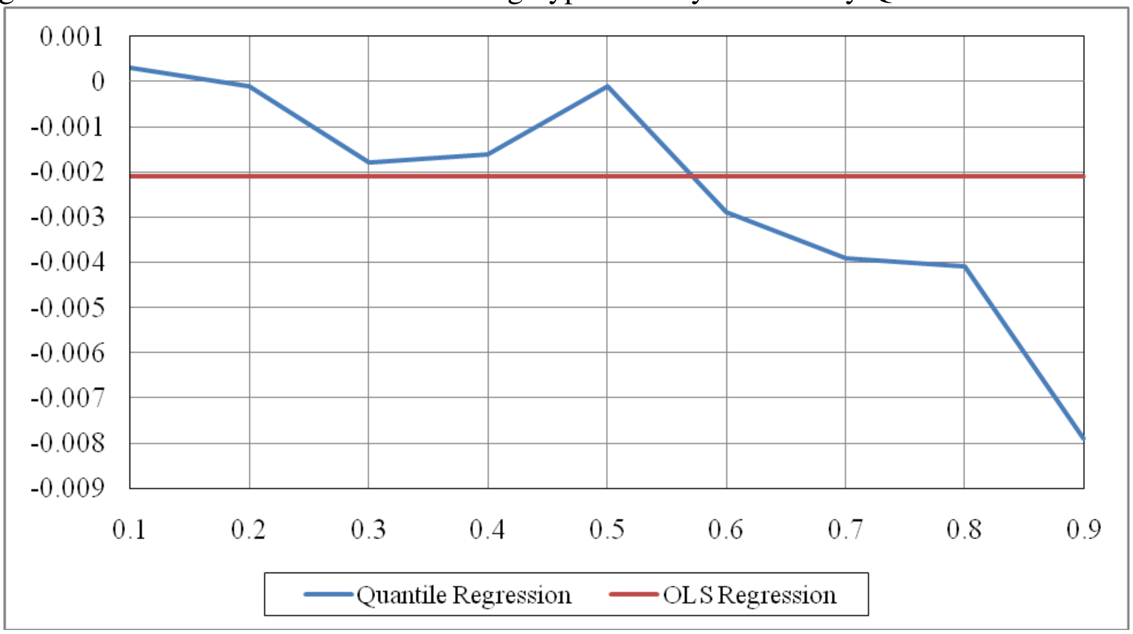

Figure 5: Estimated Parameter for Government Payments Variable by Quantile for Inefficiency u

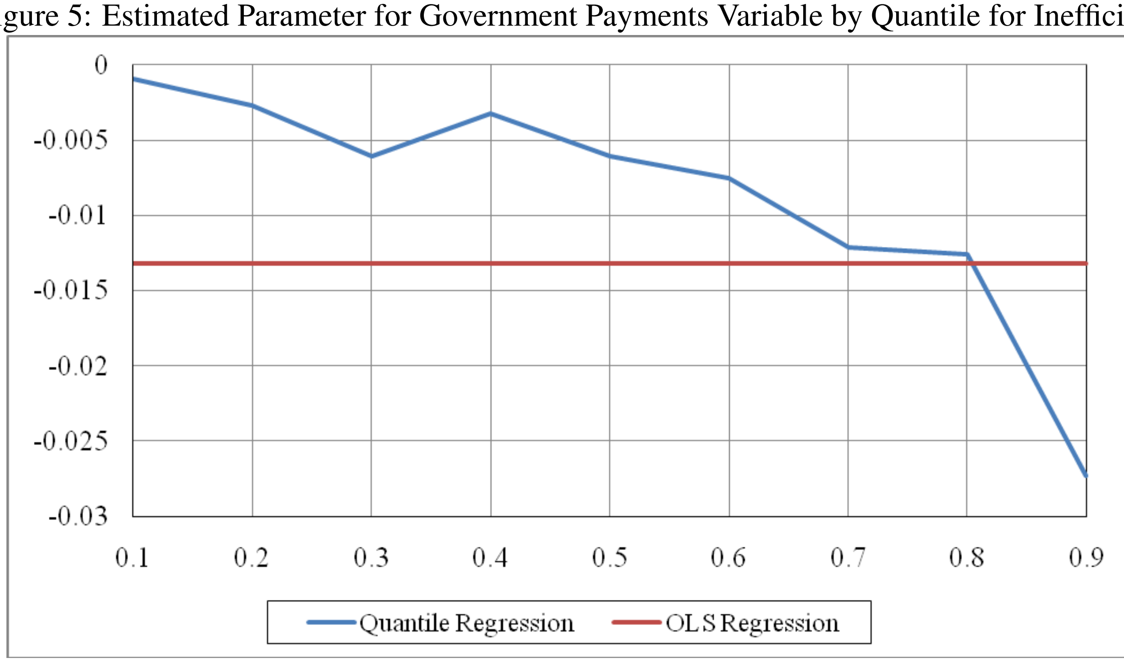

Figure 6: Estimated Parameter for Non-farm Income Variable by Quantile for Inefficiency *u*

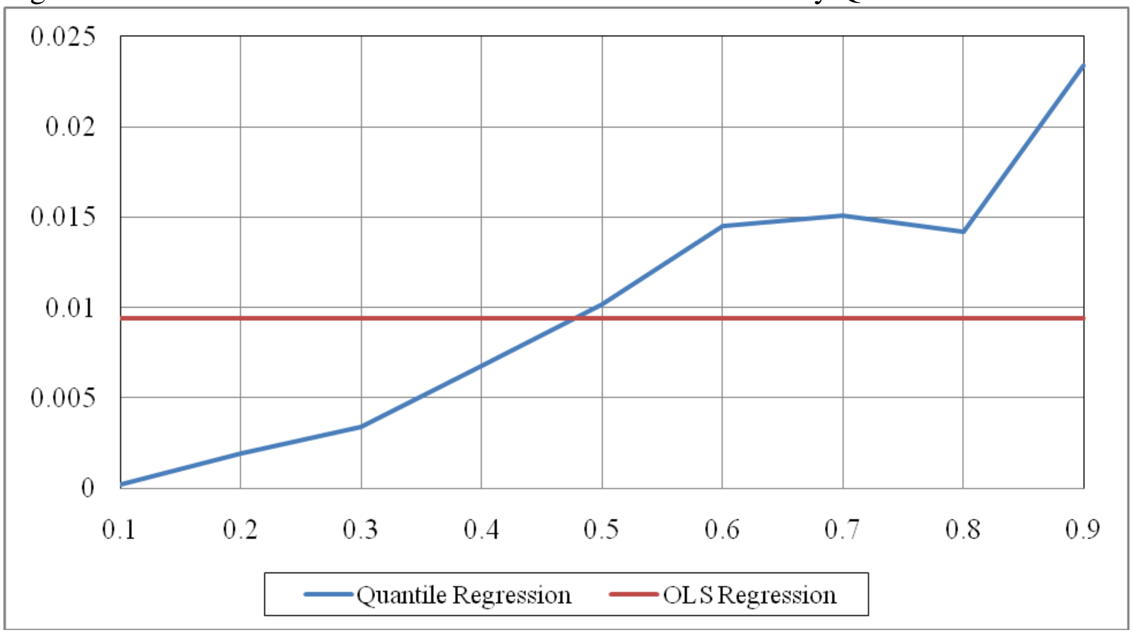

Figure 7: Estimated Parameter for Investment/CowVariable by Quantile for Inefficiency *u*

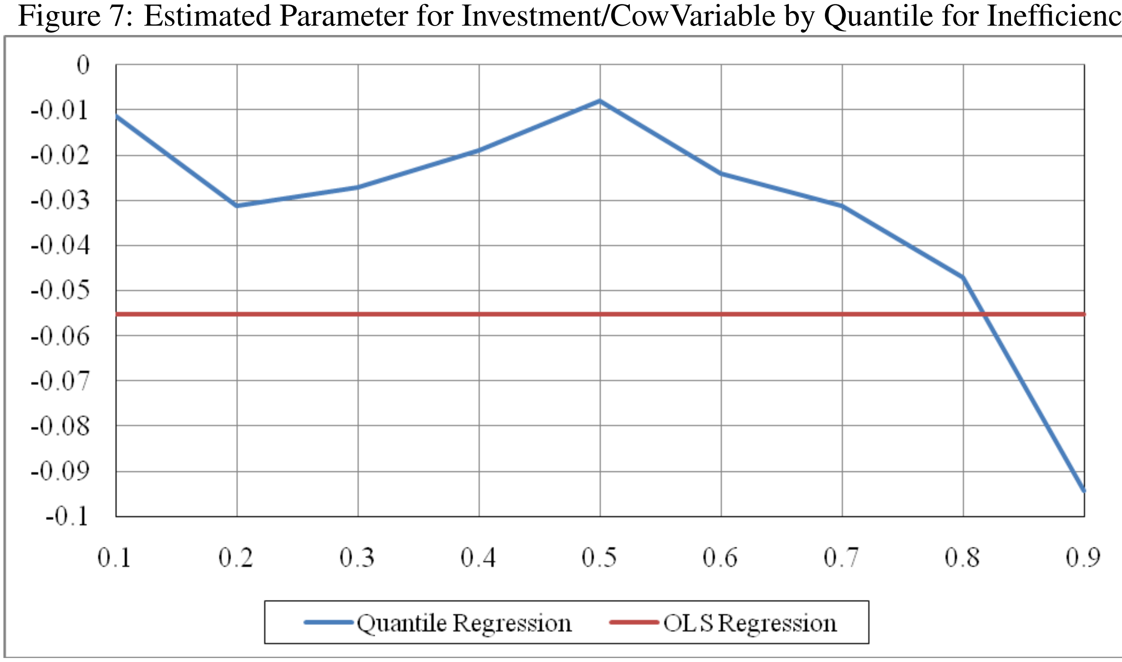

Figure 8: Estimated Parameter for Debt/CowVariable by Quantile for Inefficiency *u*

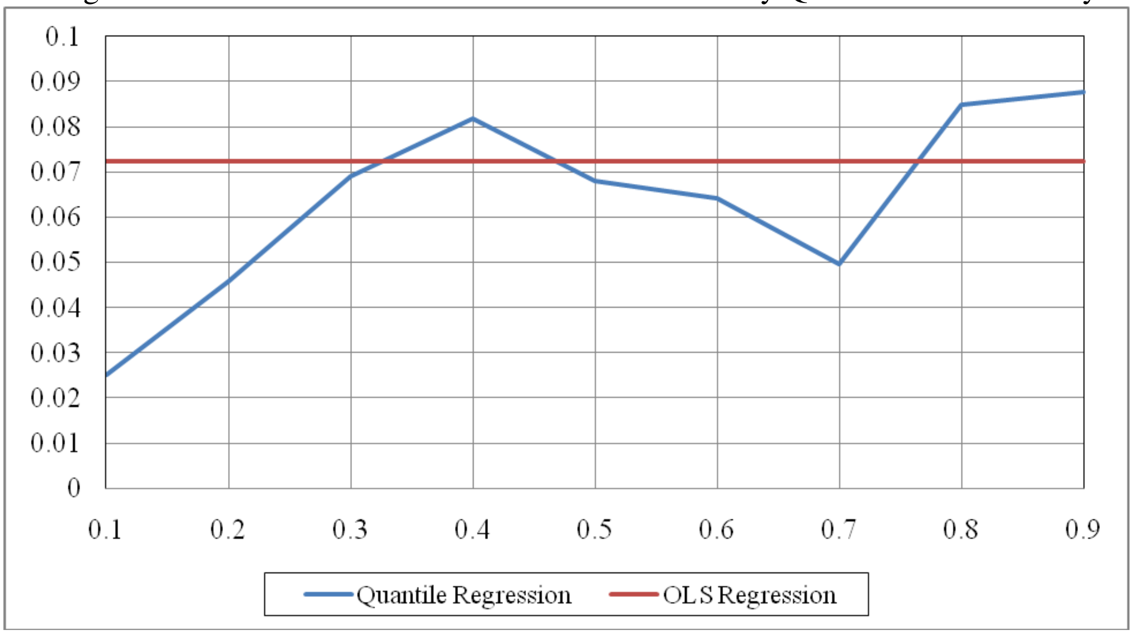

Figure 9: Estimated Parameter for Family Savings Variable by Quantile for Inefficiency *u*