Impacts of Federal Government Programs and Specific Farm

Variables on Technical Efficiency of Dairy Farms

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Abstract: In this paper technical efficiency of dairy farms is estimated using two alternative methods: data envelopment analysis and stochastic frontier analysis. Both methods provided identical ranking of states based on technical efficiency (TE) scores. Further, logistic regression is applied to TE scores to explain how known technical and policy variables affect farm's probability of being efficient.
Results of this study have shown that overall dairy farms have high TE and that there is a potential for improvement. Periodic analysis and evaluation of TE is recommended, and based on the outcomes revised production and support policies drafted.

Introduction

A great deal of change is taking place in the dairy industry; many farms are relocating from leading milk producing states to southwestern states like New Mexico, Texas, and Arizona. Some obvious reasons behind these moves are: strict state regulations on inputs used in milk production, high price of land, and favorable climatic conditions at the new location. In order to be competitive and profitable at the new location farms have to maintain high technical efficiency levels. Now days some producers can even figure out the level of technical efficiency of their farm by calculating the maximum output for a given set of inputs. However, there are many other technical factors and different kinds of programs, besides inputs and outputs that can affect technical efficiency. Agricultural Research Management Survey (ARMS) collected by ERS USDA provides large sample size of dairy farms and some additional technical variables for such study.

Federal government has been involved in regulating and subsidizing dairy industry since the 1930s. Today, the largest dairy programs include: the federal milk marketing orders program, the milk price support program, the dairy export incentive program, and the most current addition is the milk income loss contract program. We hear a lot of arguments for and against some of these dairy programs. Proponents of the current federal dairy programs are saying that without these programs we would not be able "to insure adequate supplies of milk and dairy products to meet consumers' demands" and dairy industry would not be able to survive a foreign competition (Miller and Blayney, 2006). Opponents express opinions that U.S. dairy policies harm international trade relationships and create tax burden on consumers. You can find a vast amount of literature with numbers supporting both sides of this argument. The Organization for Economic Cooperation and Development found that U.S. policies create a 26 percent "implicit tax" on milk consumers and this "tax" is causing a greater harm to the low-income families (OECD, 2005). A study by Economic Research Service of USDA found that if all milk price support programs were eliminated the short-run impact would be "decrease in farm milk price of 5-7 percent, with long term adjustment of 1 percent reduction that could be offset by higher commercial exports of nonfat dry milk" (USDA ERS, 2004). FAPRI also found that elimination of U.S. dairy price support program would have a modest impact on milk prices and production (Westhoff and Brown, 2005). To study impacts of government programs on efficiency of production we have included several variables that represent two federal government programs: milk marketing orders program and milk income loss program.

Thus, the objective of this research is to estimate technical efficiency scores and to reexamine these scores for a large number of dairy farms participated in the ARMS survey located in 24 states by considering two federal government milk programs and by considering additional technical variables offered by ARMS survey.

Theoretical Model

We applied two well established methods to estimate technical efficiency scores for all dairy farms in the data sample. First method is the stochastic frontier analysis (SFA). It is an econometric technique where you specify functional form of your model. Besides estimating technical efficiency scores, it allows you to conduct conventional hypothesis testing. Second method is a linear programming approach; it is called a data envelopment analysis (DEA).

Data Envelopment Analysis. Using DEA technical efficiency can be estimated with input- or output-oriented approach. We use output oriented approach which answers a question:" By how much output can be expanded without changing input usage?" In this case technical efficiency (θ) is measured as a ratio of obtained output to the maximum amount of output to reach the frontier. The ratio of the observed output for the i-th firm, relative to the potential output, defined by frontier, given the input vector x_i, is used to define the technical efficiency of the i-th firm:

$$TE = \frac{y_i}{\exp(x_i\beta)} = \frac{\exp(x_i\beta - u_i)}{\exp(x_i\beta)} = \exp(-u_i).$$

Technical efficiency (θ) takes values between 0 and 1. We made an assumption of constant returns to scale (CRS). The CRS assumption is much stronger assumption than the VRS assumption and since the distance to the frontier is shorter than under variable returns to scale (VRS) assumption, technical efficiency scores will be higher compared to the CRS assumption. With constant returns to scale the output oriented scores are equivalent to input oriented scores.
The output oriented technical efficiency scores were estimated by solving linear programming problem:

$$F^0(x_i, y_i | C) = max_{\theta,z} \ \theta$$

s.t. $\quad \theta, y_i \leq zM \qquad z_iN \leq x_i \qquad z_i \geq 0,$

where $F^0(x_i, y_i | C)$ is the Farrell output-oriented technical efficiency score under constant returns to scale (C), x_i is the input for producer i, , y_i is the output for producer i, and θ is the efficiency score for the i-th producer, z is a $k \ x \ 1$ vector that denotes the intensity variables or weights for the inputs that are used to construct linear production frontier, **M** is an $i \ x \ m$ matrix of outputs for a set of producers i, and **N** is an $i \ x \ n$ matrix of inputs for a set of producers i (Farrell, 1957).

Stochastic Frontier Analysis. Aigner and Chu (1968) defined a model that can be used to estimate a parametric frontier production function of Cobb-Douglas form for N firms:

$$\ln(y_i) = x_i \beta - u_i, \quad i = 1, 2, \ldots, N,$$

where $\ln(y_i)$ is the logarithm of the scalar output for the i-th firm;

x_i is a (k+1) – row vector, whose first element is "1" and the remaining elements are the logarithms of the K-input quantities used by the i-th firm;

$\beta = (\beta_0, \beta_1, \ldots, \beta_k)'$ is a (k+1)-column vector of unknown parameters to be estimated; and

u_i is a non-negative random variable, associated the technical efficiency in the production of firms in the dairy industry.

Schmidt (1976) stated that estimators proposed by Aigner and Chu are multiple likelihood estimators if u_i are distributed as exponential or half-normal random variables. Model of Aigner and Chu was criticized for being a deterministic frontier model, since it did not account for noise or measurement errors. All deviations from a frontier were interpreted as inefficiency.

Aigner, Lovell, and Schmidt (1977) and Meeusen and Van Den Broeck (1977) independently proposed the stochastic frontier production model, where an additional random error v_i was added to a non-negative random variable u_i:

$$\ln(y_i) = x_i \beta + v_i - u_i, \quad i = 1, 2, \ldots, N.$$

This random error v_i accounts for measurement errors and some random factors on the value of output variable together with u_i, which represents unspecified input variables that affect output.

Aigner, Lovell, and Schmidt (1977) assumed that v_is were independent and identically distributed (i.i.d.) normal random variables with mean zero and constant variance σ_v^2, independent of u_is which were assumed to be i.i.d. exponential or half-normal random variables.

We use SFA approach to estimate technical efficiency scores for all dairy firms and compare these scores with DEA scores. Second SFA model was used to explain technical inefficiency in milk production. Specified above stochastic production frontier model allows simultaneous estimation of causal factors which explain inefficiencies, u_is:

$$u_i = z_i \delta + w_{it},$$

where z_i are the exogenous variables that explain inefficiencies, these can be farm specific/technical characteristics and/or policy variables, δ is a vector of parameters to be estimated, and w_{it} is a random variable.

We used DEAP(version 2.1) and FRONTIER(version 4.1) software programs developed by Tim Coelli to run these models.

Logistic Analysis. Further investigation of efficiency can be done using the fact that technical efficiency is bounded between 0 and 1, and thus logistic function can be used to

link efficiency to both policy and technical variables. Table 1 contains the description of all variables included in the following logistic function.
We estimate logistic function by estimates probability that firm is efficient or has efficiency level above average by solving a following equation:

$$\text{Logit}(p_i) = \ln(p_i / 1 - p_i) = \gamma_0 + \gamma_1 \text{Class1}_i + \gamma_2 \text{Class1SM}_i + \gamma_3 \text{Class1B}_i + \gamma_4 \text{MILP}_i + \gamma_5 \text{Dage31}_i + \gamma_6 \text{Dage21}_i + \gamma_7 \text{Dmort31}_i + \gamma_8 \text{Dmort21}_i + \gamma_9 \text{Dsys41}_i + \gamma_{10} \text{Dsys31}_i + \gamma_{11} \text{Dsys21}_i + \gamma_{12} \text{Dsize41}_i + \gamma_{13} \text{Dsize31}_i + \gamma_{14} \text{Dsize21}_i + \gamma_{15} \text{R41}_i + \gamma_{16} \text{R31}_i + \gamma_{17} \text{R21}_i + \varepsilon_i,$$

where γ_0 represents the average technical efficiency, $\text{Dage31}_i = \text{Age3}_i - \text{Age1}_i$; $\text{Dage21}_i = \text{Age2}_i - \text{Age1}_i$; $\text{Dmort31}_i = \text{Mort3}_i - \text{Mort1}_i$; $\text{Dmort21}_i = \text{Mort2}_i - \text{Mort1}_i$; $\text{Dsys41}_i = \text{Sys4}_i - \text{Sys1}_i$; $\text{Dsys31}_i = \text{Sys3}_i - \text{Sys1}_i$; $\text{Dsys21}_i = \text{Sys2}_i - \text{Sys1}_i$; $\text{Dsize41}_i = \text{Size4}_i - \text{Size1}_i$; $\text{Dsize31}_i = \text{Size3}_i - \text{Size1}_i$; $\text{Dsize21}_i = \text{Size2}_i - \text{Size1}_i$; $\text{R41}_i = \text{SW}_i - \text{NE}_i$; $\text{R31}_i = \text{NW}_i - \text{NE}_i$; $\text{R21}_i = \text{SE}_i - \text{NE}_i$; and four non-categorical variables: Class1 milk price, Class1 skim milk price, Class1 butterfat price, and milk income loss payments.

Table 1. Policy and Technical Variables Included in Logistic Regression

Variable	Description	Value (1=yes, 0=otherwise)
Class1	Price of class1 milk for 2005 according to Federal Milk Marketing Orders (FMMO) program	> 0
Class 1SM	Price of class 1 skim milk for 2005 FMMO program	> 0
Class 1 B	Price of class 1 butterfat for 2005 FMMO program	> 0
MILP	Average federal milk income loss contract payments	> 0
Age1	Age of cows less than 4 years	1, 0
Age2	Age of cows between 4 and 6 years	1, 0
Age3	Age of cows greater than 6 years	1, 0
Mortality1	Number of cows that died less than 10	1, 0
Mortality2	Number of cows that died between 10 and 75	1, 0
Mortality3	Number of cows that died greater than 75	1, 0
System1	Number of hours that milking system was in use is less than 4 hours	1, 0
System2	Number of hours that milking system was in use between 4 and 12 hours	1, 0
System3	Number of hours that milking system was in use between 12 and 18 hours	1, 0
System4	Number of hours that milking system was in use greater than 18 hours	1, 0
Size1	Number of cows less than 100 per farm	1, 0
Size2	Number of cows from 100 to 300 per farm	1, 0
Size3	Number of cows between 300 and 1000	1, 0

Size4	Number of cows greater than 1000			1, 0				
NE	North-eastern region of the United States			1, 0				
SE	South-eastern region of the United States			1, 0				
NW	North-western region of the United States			1, 0				
SW	South-western region of the United States			1, 0				

Data

In this research we used data from ARMS survey collected by ERS USDA for year 2005. These data contain survey results for twenty four states. After reviewing and organizing these data and we were left with 1774 observations for our analyses. Output in this model was represented by total value of milk produced in 2005 dollars. Main inputs were land (total acres of land on dairy farm), labor (number of hours of labor per week by paid and unpaid laborers), and feed (purchased and homegrown feed in cwt). Statistics on minimum or maximum values were not allowed for disclosure in this publication, so the following Table 2 includes means and standard deviations for 24 states and does not have minimum and maximum values.

Table 2. Summary Statistics of ARMS Survey Data by State

State	Stats	Size	TVM	Labor	Land	Feed	Age	Mort.	System
Arizona	Mean	1228	4694097	2402	59	2371189	4	71	21
	StDev	1199	5087586	2465	69	8255404	1	44	3
California	Mean	862	3191088	1498	177	1711413	4	53	14
	StDev	1007	3836681	2323	488	12267548	1	104	5
Florida	Mean	1208	4880496	10976	414	1078167	4	123	18
	StDev	1136	4623961	42571	509	2510980	1	114	5
Georgia	Mean	291	1096752	947	235	237239	4	38	8
	StDev	473	2078177	1212	276	1023185	1	163	5
Idaho	Mean	192	795973	856	62	60556	5	14	9
	StDev	541	3072595	2169	167	114031	1	39	5
Illinois	Mean	198	845559	825	40	233163	4	9	7
	StDev	407	2149941	1074	74	790283	2	10	5
Indiana	Mean	176	631551	510	76	5437153	5	15	6
	StDev	324	1279275	478	143	42915989	1	39	5
Iowa	Mean	205	835522	706	52	80047	4	15	8
	StDev	299	1301087	770	59	128484	1	42	7
Kentucky	Mean	78	226713	361	89	40168	4	5	6
	StDev	49	144059	197	108	89989	2	4	2
Maine	Mean	127	539840	861	65	2723222	5	8	6
	StDev	168	743493	717	108	17261270	1	15	4
Michigan	Mean	320	1371841	1047	65	168448	4	21	10
	StDev	473	2053281	1084	194	193677	1	37	6
Minnessota	Mean	148	587121	616	62	745949	4	11	7
	StDev	202	903847	918	99	6983840	1	19	6
Missouri	Mean	217	748972	443	320	44600	5	23	6

	StDev	719	2735685	271	1002	130680	1	106	2
New Mexico	Mean	1844	6321361	1197	236	5906800	4	121	20
	StDev	1037	3558014	1642	691	17826388	1	113	5
New York	Mean	243	993005	2365	58	438371	5	15	8
	StDev	413	1827192	14597	168	3107045	1	30	6
Ohio	Mean	188	755851	940	80	70406472	5	14	8
	StDev	288	1304259	2524	180	612498760	1	26	6
Oregon	Mean	369	1450950	1457	114	609216	5	22	11
	StDev	355	1410553	1555	181	3307744	1	23	5
Pennsylvania	Mean	140	567712	735	87	83302	5	9	6
	StDev	236	1036567	1428	236	248474	1	19	5
Tennessee	Mean	120	393457	647	119	1968781	4	10	7
	StDev	106	394500	502	103	14866562	1	11	2
Texas	Mean	442	1495005	1025	270	7990484	4	25	11
	StDev	485	1981631	1054	308	47878477	1	20	5
Vermont	Mean	125	471943	610	91	60333	5	6	6
	StDev	117	487186	397	141	94418	1	6	4
Virginia	Mean	179	685474	793	106	142446	4	11	8
	StDev	147	577636	577	177	395066	1	13	5
Washington	Mean	694	2882622	932	100	207610	4	41	15
	StDev	1256	5333297	1663	168	316211	1	66	7
Wisconsin	Mean	201	849843	752	60	1127360	5	11	7
	StDev	339	1536116	988	108	11632802	1	22	6
Total	Mean	408	1554698	1396	127	4328020	4.4	29	9.72
	StDev	369	1490433	8793	224	123985835	0.26	43	1.36

Farm technical characteristics variables selected from the survey were: average age of cows in years, number of milk cows died during 2005, and number of hours that milking system was in operation per day. Very useful policy variable - total subsidies received by a farm had to be omitted, since not all farms reported/received subsidy and Cobb-Douglas or Trans-log models do not allow missing values across observations.

Two federal government programs: milk income loss program and milk marketing orders program were represented in our model. Federal Milk Income Loss (FMIL) program was represented in our model by the average milk income loss contract payments by the region (ERS USDA, 2006). Second federal program is Federal Milk Marketing Order (FMMO) program sets prices for milk products and assures dairy farmers a minimum price for their milk throughout the year. About two-third of milk is processed under Federal Marketing Orders in ten regions of a country. We used Federal Milk Order Market (FMMO) Statistics for 2005 to collect data on prices for different milk products (AMS USDA, 2005). There are four different classes of milk under FMMO program. We were able to collect three milk prices for class 1: milk price ($/cwt), skim milk price ($/cwt), and butterfat price ($/lb). Class 1 milk products are intended to be used as a beverage. We felt that three prices under class1 would be a good proxy of FMMO program in our model.

Results

FRONTIER (4.1) program was used to estimate SFA model. This program uses maximum likelihood technique for estimation. SFA approach estimates a parametric frontier production function using either Cobb-Douglas specification or trans-log specification. Likelihood ratio test had shown that Cobb-Douglas functional form was more appropriate than trans-log functional form, we rejected H_0 hypothesis of trans-log functional form in favor of H_1 Cobb-Douglas model at 5% of significance level, using critical value for LR=12.6.

Table 3 includes results for two SFA models: first model was used to determine the values of parameters of frontier production function of Cobb-Douglas form for 1774 farms, and second model was stochastic production frontier model with additional variables - z-variables. As it is seen from the Table 3 all coefficients for labor, land and feed are positively and significantly affect the output – total value of milk produced. Second model estimates TE scores and explains total value of output in terms of inefficiency with the help of additional variables – z variables. The sign of the coefficient for first variable- average age of cows in the herd is positive and statistically significant, which can be interpreted that farms with higher average age of cows in the herd exhibited increase in inefficiency (or decrease in efficiency). Mortality coefficient is negative and statistically significant, telling that greater number for mortality reduces inefficiency. This result does not seem plausible, but given coefficient for average age of cows, it can be reasoned that higher mortality will contribute to decrease in average age of cows in herd and increase efficiency. Usage of a milking system increases efficiency (or decreases inefficiency).

Two models produced efficiency scores for every dairy farm. All farms exhibited high technical efficiency in the first model. Mean value was 97.5% for the first model. However, when we added three additional explanatory variables to the model, this provided more variation among scores and reduced mean efficiency to 78.8%.

Table 3. Stochastic Frontier Cobb-Douglas Production Function Estimates

Variables	Model 1	Model 2
X variables		
Intercept	4.6897* (0.2709)	10.5222* (0.2959)
Labor	0.7412* (0.0250)	0.4145* (0.0204)
Land	0.0680* (0.0134)	0.0438* (0.0117)
Feed	0.3136* (0.0121)	0.1699* (0.0112)
Z variables		
Constant		2.6093* (0.2521)
z_1 - Average age of cows in the herd	-	0.3332* (0.0473)
z_2 - Number of cows died in 2005	-	-0.4680* (0.0129)
z_3 - Number of hours per day that milking system was used	-	-0.2730* (0.0068)
Ln likelihood function	-2115	-1658

σ^2	0.6404*	0.3804*
γ	0.0073	0.1133
μ	-0.1368	-
Mean technical efficiency	97.5%	78.8%

Notes: standard errors are shown in parentheses, * denotes significance of the values at the 1% significance level.

Technical efficiency scores were also determined using DEA approach. Following table (Table 4) provides an average scores for each state participated in the ARMS survey with two different approaches: SFA scores and DEA scores.

Table 4. Technical efficiency scores produced by SFA and DEA models by state for the year 2005.

State	SFA scores	DEA scores
Arizona	0.974	0.776
California	0.976	0.801
Florida	0.975	0.749
Georgia	0.975	0.749
Idaho	0.975	0.784
Illinois	0.975	0.793
Indiana	0.975	0.780
Iowa	0.974	0.796
Kentucky	0.975	0.771
Maine	0.974	0.756
Michigan	0.975	0.790
Minnesota	0.975	0.775
Missouri	0.975	0.776
New Mexico	0.976	0.809
New York	0.975	0.777
Ohio	0.975	0.787
Oregon	0.975	0.765
Pennsylvania	0.975	0.776
Tennessee	0.974	0.722
Texas	0.975	0.749
Vermont	0.975	0.781
Virginia	0.975	0.751
Washington	0.976	0.818
Wisconsin	0.975	0.773
Mean	0.975	0.775

From this table we can see how efficiently each state performed based on either Stochastic Frontier approach or Data Envelopment Analyses approach. Even thou SFA model produced a higher TE scores than DEA, the outcome of both analyses is the same: Washington, New Mexico, and California exhibited highest technical efficiency with both approaches. It has been a conventional wisdom that SFA scores are a bit higher than

the DEA scores and our model is not an exemption (Balcombe et al., 2006). Average TE with DEA method is 0.775 and with SFA method it is 0.975. Balcombe, Fraser, and Kim have estimated technical efficiency for Australian dairy farms with several lternative approacahes. They have found that average value of TE with DEA approach was 0.65 and SFA approach 0.77 (Balcombe et al., 2006).

Stochastic Frontier approach had showed that all farms had high efficiency scores. However, looking at TE scores for individual farms it is obvious that efficiency of scale is at work: larger farms had higher TE scores. Based on DEA scores state of Washington was a leader in being most efficient, followed by the states of New Mexico, California, Iowa, and Illinois.

In the nest step of analysis we regress technical efficiency scores estimated with DEA approach in a logistic regression against policy and technical variables specified in Table 1. This logistic model explained about 47 percent of total variation in technical efficiency. Coefficients of logistic regression for categorical and policy variables that are hypothesized to influence technical efficiency are given in Table 5. These coefficients for different variables represent the deviation of each variable from the average farm γ_0, when averaged across all variables. For example, the effect of Age1 variable is equal to $\gamma_0 - \gamma_5 - \gamma_6$, effect of Age2 is equal to $\gamma_0 + \gamma_6$, and effect of Age3 is equal to $\gamma_0 + \gamma_5$. Effect of variable mortality with three categories is interpreted similarly to the variable age. Variables: size, equipment usage, and region with four categories also interpreted similarly. As an example, the impact of variable Size1 is $\gamma_0 - \gamma_{12} - \gamma_{13} - \gamma_{14}$; Size2 is $\gamma_0 + \gamma_{14}$; Size3 is $\gamma_0 + \gamma_{13}$; and Size4 is to $\gamma_0 + \gamma_{12}$.

Coefficients of the logistic function showed significant and negative impact of the Federal Milk Marketing Orders program based on the set price for Class 1 milk, and positive and significant impact of the same program for Class 1 skim milk price, both at 95 percent significance level. Impact of the same program based on the set price for Class 1 butterfat was not significant. Impact of the second federal program was positive, but insignificant. Coefficients Dage31, R41, and R31 were significant at 99 percent confidence level, and coefficients Dmort31, Dsize41, Dsize31 were significant at 90 percent level of significance.

Coefficients of logistic regression for FMMO program have shown that price of class 1 milk set in 2005 contributed to a reduction in probability of farm being efficient. Price for class 1 skim milk increased probability of farm being efficient. Butterfat prices under the same program did not have any effect on probability of being efficient. Payments made by the federal government in accordance with federal milk income loss program did not impact probability, either.

Coefficients for age categories have shown that that greatest and most significant contribution to the increase in probability to farms' efficiency comes from Age1 category (less than 4 years old), the probability coefficient is 11.0706. Third category of age variable (greater than 6 years old) contributed significantly to the decrease in probability of a farm being efficient.

Based on the significance of coefficients for region categories North-west region contributed most to the increase in probability of a farm being efficient, followed by North-east region. South-western region contributed to the decrease in probability of

farms being efficient, and South-east location was not statistically significant in explaining probability.

Table 5. Coefficients of Logistic Regression.

Variable	Variable Name	Coefficient	t-statistics
γ_0	Intercept	10.6878	0.5183
Class1	Price of Class 1 milk FMMO program, $ per cwt	-1.0805**	-2.4954
Class1SM	Price of Class 1 skim milk FMMO program, $ per cwt	0.9424**	2.9163
Class1B	Price of Class 1 butterfat FMMO program, $ per lb	-1.8821	-0.1644
MILP	Average FMIL program payments, $	0.000047	0.6528
Dage31	Age	-0.4332***	-2.6577
Dage21	Age	0.0504	0.5228
Dmort31	Mortality	0.3183*	1.6939
Dmort21	Mortality	-0.0993	0.9111
Dsys41	Equipment usage	-0.1868	-1.1989
Dsys31	Equipment usage	-0.0449	-0.3314
Dsys21	Equipment usage	-0.0302	-0.2938
Dsize41	Number of cows per farm	-0.3751*	-1.6583
Dsize31	Number of cows per farm	0.2180*	1.7454
Dsize21	Number of cows per farm	0.2281*	1.8046
R41	Region	-0.8066***	-4.5519
R31	Region	0.5333***	3.1538
R21	Region	0.0340	0.2146

* Significant at 0.1 level, ** significant at 0.05 level, and *** significant at 0.01 level

Conclusions

The main objective of this study was to estimate technical efficiency scores for ARMS dataset and to examine the impact of two federal government milk programs and several additional technical variables offered by ARMS survey on technical efficiency.
Two identical models were estimated using two different approaches: DEA and SFA. Technical efficiency scores for 1774 dairy farms participated in USDA ARMS survey allowed ranking of an individual farms and the states. Average TE estimated using DEA method is 0.775 and using SFA method it is 0.975. Two approaches produced identical ranking.
Second SFA model contained the same input variables as the first model and explained inefficiencies of production with three additional variables: age of cows, mortality per year, and equipment usage. All variables were highly significant in explaining

inefficiency. Coefficient for age of cows and mortality per year have shown that for farms to be more efficient they have to increase mortality to reduce average age of cows to less than or equal to 4 years old. Coefficient for equipment usage has shown that increase in hours of equipment usage will increase efficiency and decrease inefficiency.

DEA analysis had shown that 45 percent of all farms had technical efficiency of 0.775 or above, and 99.55 percent of all farms had technical efficiency of 0.6 or higher. Overall all farms had a high average technical efficiency value of 0.775, but logistic model in the second part of our study had shown that there is still room for improvement of efficiency. Here, we examined how some of the known variables might impact technical efficiency by regressing TE scores estimated with DEA approach against policy variables and technical variables represented by categorical variables. Having categorical representation of variables in the logistic model has helped to see a contribution of a particular group to the increase or decrease in probability of farm being efficient. Federal milk marketing program had significant impact on probability. Price for Class 1 milk determined by this program had a negative impact on probability of a farm being efficient, whereas the price for Class 1 skim milk under the same program had a positive impact on the probability. This outcome can imply that formula used to calculate price for Class 1 milk needs some revision and possibly reformulation. Payments under milk income loss program have shown no significant impact on the probability in efficiency.

North-west region was the most efficient region, followed by North-east region. Production practices of North-western region should be studied to learn what is done differently there. Mortality of cows per year was a significant factor in efficiency improvement.

Results of this study had shown that federal and local policies, as well as production practices have to be reexamined on a regular basis to see the combined impact of all factors on the technical efficiency and to analyze the impact of individual variables and/or programs in efficiency.

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