Impact of Financial Variables on Production in Kansas Farms Efficiencies

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Abstract

This article establishes the cost-efficiency frontier and its variation over time for a sample of 610 farms in Kansas for ten consecutive years, from 1995 to 2004. The primary objective consists of examining how financially constrained firms affect cost efficiency and its components, allocative, technical and scale efficiency. Using a sample from the Kansas Farm Management Association and data envelopment analysis (DEA) technique, each farm is measured against the rest of the sample to calculate the cost efficiency frontier and other measures of efficiency per year. Two DEA financially constrained models, constrained by solvency and level of debt of the firms respectively, are compared to the basic one in which firms are non-constrained. We test whether the debt and solvency constraints are binding, and how much and in which direction they affect the level of cost efficiency, technical efficiency, allocative efficiency, and scale efficiency. Results for the farms and period studied show that financial constraints do not impede farms from achieving their level of cost efficiency. However, in the presence of financial constraints, farms' level of technical efficiency decreases whereas their level of allocative efficiency increases.

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With recent advances in technology such as new high performance seed and global pressures, farm businesses in the United States face an increasingly competitive market. Farm managers need to make correct financial, production, and marketing decisions to be economically successful.

Financial variables, especially debt incurred to purchase inputs, and the availability of capital deeply affect the structure and organization of farm production. Färe, Grosskopf and Lee (1990) examined the impact of financial constraints on farm economic performance. They use the data envelopment analysis (DEA) technique for expenditure-constrained profit maximization following Charnes, Cooper, and Rhodes (1978) and Lee and Chambers (1986). Färe, Grosskopf and Lee's (1990) research found that a quarter of the farms in their sample were financially constrained. In addition, they found that financially constrained farms on average were more efficient than financially unconstrained farms. These apparently inconsistent findings led Whittaker and Morehart (1991) to analyze a sample of 107,982 Midwestern grain farms to measure the effect of farm financial structure on cost efficiency. Using farm expenditure data and a DEA approach, they calculated cost efficiency for the same sample with three different models: a financially unconstrained model, a debt-constrained model, and an asset-constrained model. Nearly 22 percent of the farms were constrained either by debt and/or assets. Handley et al. (2001), commenting on this small sample of production efficiency and financial structure research; observe "empirical testing has not demonstrated a common pattern regarding the direction," i.e., the status of the relation of production and finance farm variables has not been yet established (Handley et al., 2001, p. 1).

We support the contention that producers should increase their focus on financial, management, and marketing decisions to achieve economic success. The ongoing rapid advances in computer technology and their application to data compilation and management are allowing economists to make new uses of DEA techniques to better evaluate firms' performance. The objective of this article is to investigate how financial variables affect production performance. We use a sample of Kansas farms to estimate a cost frontier and compare cost efficiency, allocative efficiency, scale efficiency, and technical efficiency by farm size and over time. In other words, we conducted both a cross-sectional and time series analysis of efficiency scores. We think that the two dimensions of the study, cross and time-series can make a significant contribution to clarify and understand the nature of the relation between production and financial farm structures.

Objectives

We estimate three DEA cost frontier models using expenditure data, taking advantage of the dual relationship between profit and cost. We employ an output-oriented analysis which embodies multiple outputs and multiple inputs. Model 1 uses DEA in the basic multi-output/multi-input cost minimization problem to estimate technical, allocative, scale, and cost efficiency. Model 2 uses DEA in the same context as model 1, except that a financial constraint is added which represents the total amount of annual debt for each farm. Model 3 uses a DEA-solvency constraint model. The model is similar to model 1, except that firms are constrained by the amount of working capital.

Each of the three models are estimated separately for each year from 1995 to 2004. The efficiency scores are compared for each model each year and we investigate if any of the two financial constraints imposed are binding. Then, we compare the efficiency scores each year in terms of farm size and determine if the difference is statistically significant. In addition, by comparing the efficiency scores each year we determine the pattern of these measures over time.

Literature Review

Ray (1997) defines technical efficiency, as the ability to transform physical inputs into outputs relative to the best practice frontier given current technology. As such, this concept may be affected by the size of the operation, but not prices or costs. For example, a farm operating at the best practice frontier will score 1, whereas one farm operating below the best practice levels has a score from 0 to 1. Technical efficiency can be decomposed into two components, pure technical efficiency and scale efficiency. Scale efficiency measures the effect of farm's size on efficiency by looking at the farm's maximum average productivity. Allocative efficiency measures if the input mix, given input prices and output quantities, is chosen to minimize costs so that the farm is operating at the point where marginal cost equals marginal value product. Cost efficiency is a measure of the economic performance of a farm. The efficiencies just referred to have a value that ranges from 0 to 1; where 1 refers to a fully efficiently farm (i.e., we could also say unit, organization, or decision making unit).

There is extensive literature that applies the different concepts of efficiency to fields such as banking, education and other services, hospitals, transportation, as well as many other industries. The concept of efficiency and the frontier approach have been studied by agricultural economists for both high-income and low-income countries to analyze different types of efficiency, their measure, and how government programs affect technical and allocative efficiency. Battese (1992); and Bravo-Ureta and Pinheiro (1993) have referenced numerous empirical studies of efficiency measures applied to agricultural production). Recently the fields of finance and production in agricultural economics have started collaborating to determine the connection between the financial characteristics and production efficiency. For a discussion on the topic please refer to the article by Handley et al. (2001). A small body of literature has been devoted to the study of productivity efficiency measures and farm financial characteristics[1].

The finance literature contains five theoretical justifications and similar number of empirical approaches to study the relationship between financial structure and production efficiency: agency theory, free cash flow, credit evaluation, embodied capital and adjustment cost. Nasr, Barry and Ellinger (1998) suggest the first three proposed hypothesis: the agency costs hypothesis assumes that more indebted farmers are also more technically inefficient (i.e., more debt implies more inefficiency, which indicates a negative relationship between debt and inefficiency). Free cash flow implies that more asset holdings and excess cash flows result in more relaxed management and thus more inefficiency (i.e., debt and technical efficiency follow the same direction). Under credit evaluation, efficiency is a consequence of indebtedness in the sense that more efficient farms need more investment, and thus, they have a high level of debt (positive relationship). Chavas and Aliber (1993) suggest the embodied capital hypothesis: which implies that farmers with higher debt levels guide technical change, and thus a positive relation is implied. The adjustment hypothesis formulated by Paul et al. (2000) refers to markets which are transitioning from a more subsidized agriculture to a more market-oriented one; this hypothesis implies a negative relation between debt and efficiency as less indebted farmers are supposed to be more technical efficient as they adjust more easily to the new situation[2].

In Kansas, recent studies examined the interaction of finance, management, and marketing decisions to identify economically successful farms. Nivens, Kastens, and Dhuyvetter (2002) focus on a sample of Kansas farms to study management factors and its influence in production costs as a way of increasing farm profitability. They find that price is not as important as other variables when farms want to increase profitability; but farm managers can enhance profitability by outperforming neighboring farms in terms of risk management, low cost, and other factors.

Bierlen and Featherstone (1998) investigated the effects of financial constraints (i.e. debt) in farm machinery investment. They conclude that there might be "a trade-off between financial stability and efficiency in production" (p. 434). Featherstone and Al-Kheraiji (1995) calculate a short-run variable cost function to investigate the relationship between debt and a firm's efficiency in agricultural cooperatives. Results indicate that there is no strong evidence that debt is associated with "long run suboptimal capacity"(p. 871).

Handley et al. (2001) suggest that empirical results have not supported each other; and the fact that the hypotheses do not exclude each other. The stochastic frontier model developed by Handley et al. (2001) found a negative relationship between debt/asset ratios and technical efficiency. They suggest the agency costs and adjustment costs which corroborates the conditions of United Kingdom dairy farms.

Methodology and DEA

Two groups of techniques that estimate efficient frontiers have been used with some degree of variation in their specifications: an econometric technique, and a non-statistical math programming approach. The first one, the parametric stochastic frontier approach (SFA), fit the data to a production or cost function. It estimates a best-practice frontier function where observations are allowed to depart from the frontier due to random shock or/and inefficiency (Kumbhakar and Lovell, 2000).

The second, the data envelopment analysis (DEA), is a non-parametric technique which uses mathematical programming (Ray, 2004). DEA constructs a non-stochastic production (or cost) frontier over data points, so that some observations lie on or below above the frontier (Davidova and Latruffe, 2003)[3]. DEA is defined as "a linear programming technique which identifies the *best practice* within a sample and measures efficiency based on differences between observed and best practice" (Ray, 2004, p.9). DEA has both advantages and disadvantages as no functional form is specified and fitted to the data. Its advantage is that DEA eliminates the difficulty in estimating functions with a required form (i.e. imposing economic requirements[4] to real data fitted production or cost functions). However, DEA's non-statistical foundations creates a disadvantage in that the inefficiency scores obtained should be interpreted with care as they refer to the sample they were calculated from. DEA studies have been implemented in many fields, including but not excluding, banking (Ferrier and Lovell, 1990; Fries and Taci, 2004), government services (Steering Committee for the Review of Commonwealth/State Service Provision, 1997), transport (Piacenza, 2002) and other industries or service providers. A substantial body of literature exits that studies farms' efficiency and causes for inefficiencies. Thiam, Bravo-Ureta, and Rivas (2001) compared results from 32 studies on farm technical efficiency to understand better factors of inefficiency. The studies examine agriculture from around the world, in both low-income and high-income countries.

In our study, we use an input-oriented multi-output/ multi-input DEA approach to a sample of Kansas farm data using expenditure data (i.e., prices of inputs are available). The use of expenditure data for frontier analysis and estimation of cost efficiency is explained in Ferrier and Lovell (1990).

We estimate three sets of DEA problems under constant return to scale problems solved annually for the same sample of 610 Kansas farms. We follow the study by Whittaker and Morehart (1991), where financial constraints are introduced to a basic model and specified by adding another input (i.e., debt and working capital level in our study) with zero price. Whittaker and Morehart (1991) explain that their "model is related to Fare, Grosskopf, and Lee (1990) but it employs a cost-efficiency concept" (Whittaker and Morehart, 1991, p. 96). The first set of DEA problems calculate technical efficiency, allocative efficiency, scale efficiency, and cost efficiency for a sample 610 Kansas farms annually from 1995 to 2004. This formulation of the DEA problem is called model 1. Model 1 uses 7 outputs, 10 inputs, and prices normalized to 1 in 2004 for inputs.

The second set of DEA problems use the same variables as model 1, except that total debt for each firm is added as an input to determine if the farms that are financially constrained by debt are able to achieve the optimum efficiency level; the DEA problems are referred as model 2. The third group of DEA problems (referred to as model 3) is similar to the formulation of model 2 except that working capital, the difference between current assets and current liabilities is introduced instead of a debt constraint. Both model 2 and model 3 are calculated for the same farms and years as model 1, with the same inputs and outputs except that model 2 and model 3 are financially constrained by two different measures, debt and working capital.

Given a matrix of input prices, w_j for n inputs, a matrix of input quantities x_{js} for the S farms, and a matrix y_{is} for m outputs for the sth farm, cost efficiency under constant returns to scale corresponds to the ratio of minimum cost given level of outputs and input prices to the observed farm's total cost, i.e., $CE_{js} = MC_s(y_{is}, x^*_{js}, w_{js}) / (x_{js} \bullet w_{js})$. The linear programming cost minimization DEA problem to calculate the minimum total cost given the constant return to scale assumption and the input-orientation of the problem is taken from Ferrier and Lovell (1990).

$$
\begin{aligned}
&\mathrm{MC_s}\ (\mathrm{y}_{\ is}, \mathrm{x^*}_{\ js}, \mathrm{w}_{\ js}) = \\
&\text{Minimize}_{\ X^*_{js}, \mu_S} \quad \sum_{j=1}^{n} w_{js} \bullet x^*_{js} \\
&subject \cdot to \\
&y_i \le \sum_{s=1}^{S} \mu_s \bullet y_{is}, i = 1, 2, ..., m \\
&x_{js} \ge \sum_{s=1}^{S} \mu_s \bullet x_{js}, j = 1, 2, ..., n \\
&\mu_s \ge 0, \forall_s, s = 1, 2, ..., S
\end{aligned}
\qquad (1)
$$

Problem 1 is solved for each of the 610 farms every year for each model to compute cost efficiency scores for each farm each year in the three models. μ_s is a intensity vector of constants for each farm which denotes multipliers that indicate the input levels that the farm should implement to achieve efficiency. The solution to the problem above is a vector of the optimal/minimum input combinations for the given input prices and outputs' level.

Technical efficiency is independent of input prices. It is computed for each farm each year for every model using the following input-oriented minimization problem under the constant returns to scale assumption. If farms are technically fully efficient, κ_1 equals 1 for each farm. If $\kappa_1 > 1,$ then the farm lies below the frontier and is not fully technically efficient.

$$
\begin{aligned}
&\text{Minimize}_{\ \kappa_1, \mu_S} \quad \kappa_1 \\
&subject \cdot to \\
&y_i \le \sum_{s=1}^{S} \mu_s \bullet y_{is}, i = 1,2,...,m \\
&x_{js} \bullet \kappa_1 \ge \sum_{s=1}^{S} \mu_s \bullet x_{js}, j = 1,2,...,n \\
&\mu_s \ge 0, \forall_s, s = 1,2,...,S
\end{aligned}
\qquad (2)
$$

Following Farrel (1957), allocative efficiency is calculated for each farm each year in every model as the ratio of cost efficiency to technical efficiency. Scale efficiency is determined as the ratio of technical efficiency under constant returns to scale to technical efficiency under variable returns to scale; the last measure is referred as pure technical efficiency. The DEA problem minimization is similar to problem 2 with the additional constraint that for all farms every year the intensity vector μ is equal to one, i.e. $\sum_{s=1}^{S} \mu_s = 1$.

Data

The data sample consists of 10 years cross-section of a sample from the Kansas Farm Management Association (KFMA) of 610 farms whose data was collected from 1995 to 2004. A summary statistic of the all data is available in table 1. We have 7 outputs and 10 inputs. Outputs include: small grain production, feed grain production, oilseed production, hay and forage production, beef production, milk production, and miscellaneous income. Inputs include: hired and operator labor, feed and veterinary, seed, crop insurance, fertilizer, herbicide and insecticide, repairs and machine hire, fuel and utilities, rent, interest and depreciation, and conservation, property taxes, and fees. Not all farms produce or use all outputs or inputs.

Most of the farms in this data sample are comprised of commercial farms. The average gross income is more than $200,000 with a minimum value of $1,600 and a maximum of more than $1 million. Average acreage is 1,766 with a minimum of 33 acres and a maximum of nearly 10,000 acres. The average debt for all farms for all years is nearly $219,000 with a maximum of $2.5 million and a minimum of $0. Working capital for all the farms all years was more than $100,000.

An average of each farm over the 10 years sample helps divide farms into four classes according to their size (i.e. gross income). Table 2 shows that out of a total of 610 farms, 46% of farms in the sample have an annual average gross income between $100,000 and $250,000. Nearly 23% and 24.5% of farms have an annual average gross income between $250,000 and $500,000, and less than $100,000, respectively. Only 6.5% of farms in the sample have more than $500,000 annual average gross income.

Results

Cost efficiency and its three components are calculated for each farm for each of the three models yearly. For each year, Models 1, 2, and 3 are estimated separately for each of the 610 farms. In total, we have three solutions with 610 observations yearly from 1995 to 2004. Table 3 illustrates the difference of the efficiency scores between models. Neither cost efficiency nor scale efficiency statistically differ between model 1 and model 2, and model 1 and model 3. The farms appear to achieve the same level of efficiency despite being debt constrained or/and working capital constrained in any of the years from 1995 to 2004. However, financially constrained models 2 and 3 differ in the estimates of technical efficiency and allocative efficiency. The comparison between the basic model 1 and the debt constraint model 2 or working capital constraint model 3 respectively, report the same direction in the move of the allocative efficiency and technical efficiency estimates in the presence of financial stress. There is an inverse relation for most years between the technical efficiency and allocative efficiency scores in models 2 and 3 when compared with scores in model 1. The results for the statistically significant difference (at the 5 % confidence level) in technical efficiency and allocative efficiency cores between financially-constrained models 2 and 3 and base model 1 suggests that there exist a negative relationship between technical efficiency and the cost structure of a farm. On the contrary, allocative efficiency seems to be positively related to more indebted farms or those with negative working capital. The results suggest that for farms in this sample that the financial constraints did not prevent the farms from achieving overall cost efficiency. When farms were constrained by debt or negative working capital they compensated the level of technical efficiency and allocative efficiency to maintain the level of cost efficiency. This finding supports the hypothesis that cost structure does influence production efficiency.

In table 4 we compile summary statistics for the results of technical efficiency, allocative efficiency, scale efficiency, and cost efficiency scores estimated with model 1 for all the farms for the 10 years. In general, results show that sample farms could improve their overall economic performance by 35 percent producing the same level of output. The average level of the farms' technical efficiency is close to 94 percent, followed by nearly 90 percent scale efficiency. As far as allocative efficiency and the farms' input mix, the level of efficiency could be more than 20 percent higher. Table 5 provides an average estimate of all the farms per year for cost efficiency estimates. It shows the percentage of farms whose cost efficiency score is 1, i.e., totally efficient farms per year. Farms fully cost efficient are the highest with 5.6 percent in 1996 and 2001; the number of fully cost efficient farms drops to its lowest with 2.46 in 1999. Mean scores for all farms cost efficiency estimates by year is subject to little variability, scores range from a maximum of 0.7032 in 1998 to a minimum of 0.6240 in 2000.

The relationship between financial exposure and farm productivity is explored by specifying a model is consistent with the inverse relation between technical efficiency and allocative efficiency in the presence of financial constraints. As an example, table 6 illustrates a least square model where working capital explains 5 per cent of the change in allocative efficiency between model 1 and model 3 in 1995.

Further investigation of the efficiency scores permit us to decompose these measures into four categories that refer to farms size in terms of gross annual income. Tables 7, 8, and 9 illustrate an annual statistical analysis on the scores obtained with models 1, 2, and 3, respectively. Consistently every year, farms earning more than $500,000 have a scale efficiency smaller than the average scale efficiency score for farms whose gross income is between $250,000 and $500,000. For most years, farms whose gross income is more than $500,000 have an average technical efficiency, allocative efficiency and cost efficiency larger than the corresponding ones for the category of farms whose gross income is between $250,000 and $500,000.

Farms with gross incomes ranging from $100,000 to $250,000 compared to farms with less than $100,000 consistently have mean values of cost efficiency and scale efficiency that is larger over the entire period. For most years, allocative efficiency is also larger. However, the difference in technical efficiency scores is not statistically different for these two categories of farms.

The results of efficiency estimates support the claim of a relationship between cost structure and farm production performance, and a negative relation between financial structure and technical efficiency. This fact is consistent with findings in prior literature (Handley et al., 2001, Paul, et al., 2000). Furthermore, we agree with Bierlen and Featherstone, 1998 that cost exposure affects production efficiency scores. This is especially true as technical efficiency and allocative efficiency offset each other to leave cost efficiency unchanged after the new cost structure (i.e., adding debt or negative working capital as a farm constraint, or exposing the farm cost structure).

Disaggregating the efficiency scores according to farm sizes provided information on the relationship that farm size has with cost and production efficiency measures. The findings are conclusive for the farm sample. There appears a pattern of change for Kansas farms between 1995 and 2004, where larger farms score higher in most efficiency scores except for scale efficiency.

Conclusions

The purpose of this study was to investigate how financial variables affect production performance. Using a sample of 610 Kansas farms, we have estimated cost frontiers yearly from 1995 to 2004 and compare cost efficiency, allocative efficiency, scale efficiency and technical efficiency scores among farms across years for a basic model and for two financially-constrained models.

Three DEA models with the same 610 farms' data were estimated for 10 years. The basic model 1 consisted of an input-oriented multi-output/multi-input cost frontier. Models 2 and 3 used the same specification as model 1 except that farms were constrained by total debt and working capital, respectively. We did not find a significant difference between the annual results obtained for debt-constrained model 2 and working capital-constrained model 3. Cost efficiency and scale efficiency scores did not differ statistically across models. We found that technical efficiency and allocative efficiency scores differ annually between the base model 1 and the debt-constrained model 2 and working capital-constrained model 3 (with some minor changes between technical efficiency and allocative efficiency scores in models 2 and 3). In general, scores for technical efficiency are smaller when farms are financially constrained than when they are not, whereas scores for allocative efficiency are larger when farms are financially constrained. Our article supports prior literature that a negative relation between farms' financial exposure and technical efficiency. Additionally, comparing technical efficiency, allocative efficiency, scale efficiency, and cost efficiency results show that characteristics such as farm's size influence that relationship.

End Notes

[1] Some others like Handley et al. (2001), and Davidova and Latruffe (2003) refer to this relationship in more narrowed terms like technical efficiency and financial farm exposure.

[2] For more information about these theories see Handley et al. (2003) and Davidova and Latruffe (2003)

[3] For a more detailed explanation on the estimation and varieties of DEA see Charnes, Cooper and Rhodes (1978); and Färe, Crosskopf and Lovell (1994).

[4] Requirements are symmetry, homogeneity, curvature, and so on.

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Table 1. All Farms' Financial and Size Data.

Average Values (all farms,	Observati	Mean	Standard	Minimu	Maxim
Farm Characteristics					
Number of units (DMU)/	6100			1	610
Year	6100			95	104
Gross Farm Income ($)	6100	219,95	195,328	1,600	1,697,3
Total Acres	6100	1,766	1,228	33	9,573
Total Assets ($)	6100	752,99	582,075	40,587	7,011,3
Total Debt ($)	6100	218,96	257,929	0	2,447,3
Working Capital ($)	6100	100,57	167,861	-	1,671,7
Outputs					
Small Grain Prod. (Bu)	6100	10,493	13,594	0	138,242
Feed Grain Prod. (Bu)	6100	18,984	27,543	0	245,589
Oilseed Prod. (Bu)	6100	5,767	9,073	0	114,100
Hay and Forage Prod.	6100	92	239	0	4,639
Beef Prod. (Pounds)	6100	67,731	124,717	0	1,685,4
Dairy Prod. (Pounds)	6100	143,84	629,768	0	7,029,7
Miscellaneous ($)	6100	14,871	32,066	0	574,564
Inputs					
Labor	6100	53,379	29,774	3,998	265,772
Feed and Vet.	6100	30,634	64,901	0	760,224
Seed	6100	17,045	19,357	0	215,881
Crop Insurance	6100	3,577	4,902	0	86,395
Fertilizer	6100	23,533	23,835	0	236,483
Herbicide and Insecticide	6100	13,772	15,094	0	123,620
Repairs and Machine Rent	6100	31,402	28,580	662	434,364
Fuel	6100	21,082	20,025	91	187,648
Others	6100	7,033	6,170	0	78,854
Interest and Depreciation	6100	75,243	58,007	4,076	622,075
Real Input Prices (normalized to 1 in 2004)					
Labor	6100	0.927	0.059	0.8400	1.0000
Feed and Vet.	6100	1.018	0.100	0.9100	1.2300
Seed	6100	0.893	0.061	0.8200	1.0000
Crop Insurance	6100	1.000	0.000	1.0000	1.0000
Fertilizer	6100	0.921	0.077	0.8000	1.0300
Herbicide and Insecticide	6100	1.093	0.054	1.0000	1.1500
Repairs and Machine Rent	6100	0.985	0.011	0.9700	1.0000
Fuel	6100	0.758	0.124	0.5800	1.0000
Others	6100	1.031	0.039	0.9800	1.1200
Interest and Depreciation	6100	1.000	0.000	1.0000	1.0000

Table 2. All Farms: Annual Mean Gross Income from 1995 to 2004.

Dollars	< $100,000	$100,000- $250,000	$250,000- $500,000	< $500,000
Percentage	24.5%	46%	23%	6.5%
Income	$67,005	$165,822	$345,030	$732,182

Table 3. Mean Efficiency Differences between Models.

Year		M1-2	M1-3	M2-3	Year		M1-2	M1-3	M2-3
1995	**ΔTE**	-	D<0	-	**2000**	**ΔTE**			D<0
	ΔAE	D>0	D>0	-		**ΔAE**			D>0
	ΔSE	-	-	-		**ΔSE**			-
	ΔCE	-	-	-		**ΔCE**			-
1996	**ΔTE**	-	D<0	-	**2001**	**ΔTE**	-	D<0	-
	ΔAE	D>0	D>0	-		**ΔAE**	D>0	D>0	-
	ΔSE	-	-	-		**ΔSE**	-	-	-
	ΔCE	-	-	-		**ΔCE**	-	-	-
1997	**ΔTE**	D<0	-	-	**2002**	**ΔTE**	D<0	D<0	-
	ΔAE	D>0	D>0	-		**ΔAE**	D>0	D>0	-
	ΔSE	-	-	-		**ΔSE**	-	-	-
	ΔCE	-	-	-		**ΔCE**	-	-	-
1998	**ΔTE**	-	D<0	-	**2003**	**ΔTE**	D<0	D<0	-
	ΔAE	D>0	D>0	-		**AE**	D>0	D>0	-
	ΔSE	-	-	-		**ΔSE**	-	-	-
	ΔCE	-	-	-		**ΔCE**	-	-	-
1999	**ΔTE**	D<0	D<0	D<0	**2004**	**ΔTE**	D<0	D<0	-
	ΔAE	D>0	D>0	D>0		**ΔAE**	D>0	D>0	-
	ΔSE	-	-	-		**ΔSE**	-	-	-
	ΔCE	-	-	-		**ΔCE**	-	-	-

Notes: - denotes the differences between the scores are not statistically different than zero at the 5% confidence level. . Δ= is the Greek letter delta, meaning change, or difference. D>0 and D<0 denotes the differences between scores are statistically significantly larger than zero, and smaller than zero respectively.

Table 4. Statistics for DEA Efficiency Scores Model 1 for All Farms from 1995 to 2004.

Efficiency	Mean	Standard Deviation	Minimum	Maximum
Cost	0.648	0.186	0.060	1
Technical	0.940	0.109	0.340	1
Allocative	0.765	0.144	0.207	1
Scale	0.895	0.128	0.097	1

Table 5. DEA Cost Efficiency Estimates Model 1 by Year.

Year	Mean	Number/%	Year	Mean	Number/%
1995	0.6463	31/5.08	2000	0.6240	21/3.44
1996	0.6401	32/5.24	2001	0.6905	32/5.24
1997	0.6647	28/4.59	2002	0.6913	25/4.09
1998	0.7032	21/3.44	2003	0.6933	18/2.95
1999	0.6317	16/2.62	2004	0.6760	22/3.60

Table 6. Least Square Regression of ΔAE and Working Capital in 1995.

Dependent variable ΔAE95	Coefficient	Standard Error	t- Value	P>t
Working Capital in 1995	4.86E-08	8.01E-09	6.07	0
Constant	-0.0148349	0.00145	-10.21	0

Notes: The adjusted R-squared of the model is 0.0555. ΔAE refers to the difference between allocative efficiency scores in model 1 and model 2

Table 7. Farms by Average Size over 10 Years Period, Base Model 1.

Year	Efficiency	>$.500 Th.	$500-250	$250-100	< $100	All
1995	**Technical**	0.9818*	0.9489	0.9401	0.9288	0.9499
	Allocative	0.8745*	0.7767	0.7314*	0.6606	0.7608
	Scale	0.8744**	0.9700	0.9414*	0.7640	0.8875
	Cost	0.7449	0.7176	0.6497*	0.4727	0.6463
1996	**Technical**	0.9769*	0.9629	0.9145	0.9274	0.9454
	Allocative	0.8910*	0.7738	0.7339	0.6927	0.7728
	Scale	0.8795**	0.9562	0.9313*	0.7213	0.8721
	Cost	0.7621	0.7111	0.6263*	0.4608	0.6401
1997	**Technical**	0.9755	0.9477	0.9148	0.9292	0.9418
	Allocative	0.8889*	0.8026	0.7487*	0.6894	0.7824
	Scale	0.9146**	0.9648	0.9353*	0.7589	0.8934
	Cost	0.7945	0.7357	0.6460*	0.4827	0.6647
1998	**Technical**	0.9893*	0.9676	0.9311	0.9290	0.9543
	Allocative	0.9357*	0.8127	0.7837*	0.7324	0.8161
	Scale	0.8867**	0.9590	0.9583*	0.7899	0.8985
	Cost	0.8204*	0.7542	0.7016*	0.5365	0.7032
1999	**Technical**	0.9961*	0.9397	0.9100	0.9250	0.9427
	Allocative	0.9019*	0.7446	0.7240	0.6980	0.7671
	Scale	0.8816**	0.9499	0.9197*	0.7156	0.8667
	Cost	0.7866*	0.6628	0.6098*	0.4677	0.6317
2000	**Technical**	0.9961*	0.9453	0.9193	0.9296	0.9511
	Allocative	0.9118*	0.7595	0.7362*	0.7104	0.7605
	Scale	0.8993**	0.9703	0.9328*	0.7278	0.8866
	Cost	0.8001*	0.6720	0.6204*	0.4757	0.6398
2001	**Technical**	0.9969*	0.9729	0.9408	0.9461	0.9642
	Allocative	0.9141*	0.8005	0.7722*	0.7341	0.8052
	Scale	0.8894**	0.9561	0.9413*	0.7602	0.8867
	Cost	0.8079*	0.7426	0.6862*	0.5251	0.6905
2002	**Technical**	0.9803	0.9624	0.9336	0.9332	0.9524
	Allocative	0.9264*	0.8080	0.7761*	0.7259	0.8091
	Scale	0.8691**	0.9572	0.9463*	0.7971	0.8924
	Cost	0.7882	0.7448	0.6885*	0.5436	0.6913
2003	**Technical**	1.0000	0.9805	0.9385	0.9388	0.9645
	Allocative	0.9264*	0.8245	0.7788*	0.7586	0.8221
	Scale	0.8331**	0.9627	0.9411*	0.7502	0.8718
	Cost	0.7669*	0.7792	0.6910*	0.5363	0.6933
2004	**Technical**	0.9983*	0.9510	0.9302	0.9279	0.9518
	Allocative	0.9110*	0.7931	0.7715*	0.7244	0.8000
	Scale	0.8759**	0.9591	0.9370*	0.7547	0.8817
	Cost	0.7903	0.7248	0.6745*	0.5144	0.6760

Notes: * denotes the differences between the efficiency scores marked with the asterisk and the scores in the in the right column are significantly greater than zero at 5 % confidence level. ** denotes the differences between the efficiency scores are significantly less than zero at 5 % confidence level.

Table 8. Farms by Average Size over 10 Years Period, Debt-Constrained Model 2.

		Mean Efficiency Scores				
Year	**Efficiency**	**> $500 Th.**	**$500-250**	**$250-100**	**<$100**	**All**
1995	**Technical**	0.9824	0.9560	0.9451	0.9504	0.9585
	Allocative	0.8740	0.7707	0.7276	0.6454	0.7544
	Scale	0.8744	0.9700	0.9414	0.7640	0.8875
	Cost	0.7449	0.7176	0.6497	0.4727	0.6463
1996	**Technical**	0.9809	0.9680	0.9246	0.9437	0.9543
	Allocative	0.8887*	0.7695	0.7262*	0.6800	0.7661
	Scale	0.8795**	0.9562	0.9313*	0.7213	0.8721
	Cost	0.7621	0.7111	0.6263	0.4608	0.6401
1997	**Technical**	0.9771	0.9549	0.9274	0.9527	0.9530
	Allocative	0.8876*	0.7969	0.7389*	0.6704	0.7734
	Scale	0.9146**	0.9648	0.9353*	0.7589	0.8934
	Cost	0.7945	0.7357	0.6460	0.4827	0.6647
1998	**Technical**	0.9898*	0.9739	0.9404**	0.9470	0.9628
	Allocative	0.9353*	0.8077	0.7763*	0.7169	0.8091
	Scale	0.8867*	0.9590	0.9583*	0.7899	0.8985
	Cost	0.8204**	0.7542	0.7016	0.5365	0.7032
1999	**Technical**	0.9924*	0.9422	0.9157**	0.9429	0.9483
	Allocative	0.8988*	0.7838	0.7524*	0.7107	0.7864
	Scale	0.8576**	0.9664	0.9197*	0.7228	0.8666
	Cost	0.7592*	0.7131	0.6354*	0.4827	0.6476
2000	**Technical**	0.9961*	0.9453	0.9193**	0.9436	0.9511
	Allocative	0.9019*	0.7395	0.7162*	0.6846	0.7605
	Scale	0.8816**	0.9499	0.9197*	0.7156	0.8667
	Cost	0.7866*	0.6628	0.6098*	0.4677	0.6317
2001	**Technical**	0.9969*	0.9789	0.9476	0.9654	0.9722
	Allocative	0.9141*	0.7955	0.7667*	0.7191	0.7988
	Scale	0.8894**	0.9561	0.9413*	0.7602	0.8867
	Cost	0.8079*	0.7426	0.6862*	0.5251	0.6905
2002	**Technical**	0.9853	0.9677	0.9472**	0.9626	0.9657
	Allocative	0.9232*	0.8041	0.7653*	0.7029	0.7989
	Scale	0.8691**	0.9572	0.9463*	0.7971	0.8924
	Cost	0.7882	0.7448	0.6884*	0.5436	0.6913
2003	**Technical**	1.0000	0.9817	0.9477	0.9557	0.9713
	Allocative	0.9264*	0.8232	0.7717*	0.7447	0.8165
	Scale	0.8331**	0.9627	0.9411*	0.7502	0.8718
	Cost	0.7669*	0.7789	0.6913*	0.5363	0.6933
2004	**Technical**	0.9994*	0.9549	0.9401	0.9517	0.9615
	Allocative	0.9101*	0.7904	0.7638*	0.7047	0.7923
	Scale	0.8759**	0.9591	0.9370*	0.7547	0.8817
	Cost	0.7903	0.7248	0.6747*	0.5144	0.6760

Notes: * denotes the differences between the efficiency scores marked with the asterisk and the scores in the in the right column are significantly greater than zero at 5% confidence level. ** denotes the difference between the efficiency scores is significantly less than zero at 5 % confidence level.

Table 9. Farms by Average Size over 10 Years Period, Working Capital-Constrained

		Mean Efficiency Scores				
Year	**Efficiency**	**> $500 Th.**	**$500-250**	**$250-100**	**<$100**	**All Farms**
1995	**Technical**	0.9840	0.9538	0.9500	0.9358	0.9559
	Allocative	0.8726	0.7723	0.7228	0.6555	0.7558
	Scale	0.8744	0.9700	0.9414	0.7640	0.8875
	Cost	0.7449	0.7176	0.6497	0.4727	0.6463
1996	**Technical**	0.9911*	0.9740	0.9294	0.9389	0.9583
	Allocative	0.8806*	0.7659	0.7210	0.6834	0.7627
	Scale	0.8795**	0.9562	0.9313*	0.7213	0.8721
	Cost	0.7621	0.7111	0.6263*	0.4608	0.6401
1997	**Technical**	0.9757	0.9560	0.9263	0.9380	0.9490
	Allocative	0.8888*	0.7963	0.7395*	0.6821	0.7767
	Scale	0.9146**	0.9648	0.9353*	0.7589	0.8934
	Cost	0.7945	0.7357	0.6460*	0.4827	0.6647
1998	**Technical**	0.9911*	0.9735	0.9404	0.9360	0.9603
	Allocative	0.9343*	0.8080	0.7758*	0.7263	0.8111
	Scale	0.8867**	0.9590	0.9583*	0.7899	0.8985
	Cost	0.8204*	0.7542	0.7016*	0.5365	0.7032
1999	**Technical**	0.9930*	0.9584	0.9318	0.9287	0.9530
	Allocative	0.8983*	0.7702	0.7383	0.7222	0.7823
	Scale	0.8576**	0.9664	0.9197*	0.7228	0.8666
	Cost	0.7592*	0.7131	0.6354*	0.4827	0.6476
2000	**Technical**	0.9981*	0.9535	0.9298	0.9358	0.9543
	Allocative	0.9001*	0.7344	0.7081	0.6897	0.7581
	Scale	0.8816**	0.9499	0.9197*	0.7156	0.8667
	Cost	0.7866*	0.6628	0.6098*	0.4677	0.6317
2001	**Technical**	0.9969*	0.9789	0.9483	0.9568	0.9702
	Allocative	0.9141*	0.7960	0.7660*	0.7259	0.8005
	Scale	0.8894**	0.9561	0.9413*	0.7602	0.8867
	Cost	0.8079*	0.7426	0.6862*	0.5251	0.6905
2002	**Technical**	0.9817	0.9735	0.9479	0.9406	0.9609
	Allocative	0.9246*	0.7992	0.7640*	0.7203	0.8020
	Scale	0.8691**	0.9572	0.9463*	0.7971	0.8924
	Cost	0.7882	0.7448	0.6884*	0.5436	0.6913
2003	**Technical**	1.0000*	0.9862	0.9564	0.9509	0.9734
	Allocative	0.9264*	0.8194	0.7641*	0.7488	0.8147
	Scale	0.8331**	0.9627	0.9411*	0.7502	0.8718
	Cost	0.7669*	0.7789	0.6910*	0.5363	0.6933
2004	**Technical**	0.9984*	0.9627	0.9460	0.9371	0.9611
	Allocative	0.9109*	0.7822	0.7580*	0.7172	0.7921
	Scale	0.8759**	0.9591	0.9370*	0.7547	0.8817
	Cost	0.7903	0.7248	0.6745*	0.5144	0.6760

Notes: * denotes the differences between the efficiency scores marked with the asterisk and the scores in the in the right column are significantly greater than zero at 5 % confidence level. ** denotes the differences between the efficiency scores are significantly less than zero at 5 % confidence level.