Sources of Inefficiency in Kansas Farms

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Abstract

This paper uses two different techniques to measure efficiency in a panel of two hundred multi-product Kansas farms from the period 1984 to 2004. The non-parametric linear programming technique, Data Envelopment Analysis (DEA); and a parametric stochastic frontier approach, a translog production function, are used to calculate and then compare efficiencies measures including pure efficiency, technical, scale and allocative. Production, financial, and demographic variables are used to identify and quantify the causes of inefficiencies. We expect to find variables such as hours of family labor, owned versus rented farm, intensity of production, farmers´ risk attitudes and farmers´ age, significant in explaining farm inefficiency levels in Kansas farms.

Key words: Data Envelopment Analysis, Technical Efficiency

Introduction

The production frontier approach has been widely used to measure efficiency in agricultural economics since the eighties. It has been applied to numerous studies using farm level data, especially farm data in low and high income countries. Battese (1992) and Coelli (1995) developed empirical applications of the frontier approach to study efficiency at the farm level.

The stochastic frontier approach (SFA) differentiates between empirical methods that examine either movements towards the best-practice frontier or shifts in technology. Both methods of the production frontier approach are used in this study, because each has advantages and disadvantages over the other. The first technique is a non-parametric linear programming technique (Data Envelopment Analysis, DEA), which does not impose restrictions on the data. The second technique is a parametric stochastic production frontier (SFA) approach. Most studies use the translog function to represent the actual data, but we will also use a normalized quadratic function to check and correct for the appropriate curvature in the function. Both function specifications using SFA provide numerical differentiation in the efficiency scores between random error and systematic error.

Next, one step and two step procedures will be used to determine and examine the determinants of inefficiency. In the two step procedure we investigate the determinants of farm inefficiency by regressing inefficiency scores by a vector of farm-specific characteristics. The one step procedure, as implemented by Battese and Coelli (1995), allows for simultaneous estimation of the parameters of the stochastic frontier function and the inefficiency model.

This paper is innovative in that it uses detailed, farm-level panel data to measure inefficiency and its sources using two comparative methods. Panel data helps identify better estimates of inefficiency because the approach includes individual farm factors that affect inefficiency; and, which are otherwise difficult to account for such as soil type and farm management practices. Importantly, the richness of the data set will allow us to contrast the two different empirical techniques to measure inefficiency scores and investigate their sources in multi-product farms. Specific objectives include:

- Calculate standard measures of efficiency, i.e. pure efficiency, technical, scale and allocative using DEA
- Calculate the same measures of efficiency cited above using a stochastic frontier approach, in particular a translog production function
- Compare the results and explain the difference, if any, between the measures obtained using the two techniques
- Use a two-step procedure as Battese and Coelli (1995) to estimate the determinants of farm inefficiencies dependant on production, financial, and demographic variables
- Use a Tobit regression with the same aim as above to compare results between the two methods
- Use results of the empirical estimation to set some light and develop strategies that can improve Kansas farms efficiency levels

This study proceeds in the following way. The next section reviews the literature in farm finance and production efficiency followed by an account of DEA methodology and the SFA approach. We then describe the data used in the study. We end by summarizing results and drawing conclusions.

Background Literature

The concept of efficiency is intrinsically related to the estimation of a frontier since efficiency measurements can only be derived with respect to a benchmark, i.e. an ideal level of performance or best practice frontier. In estimating this unobservable benchmark or frontier, production or cost (dual approach) specifications have been used. Technical efficiency refers to a firm's ability to transform physical inputs to outputs relative to the best practice frontier (i.e. given current technology, no waste in production and so on). As such, this concept is very much affected by scale or size of the firm, but not output prices or input costs (Kumbhakar and Lovell, 2000). For example, a farm operating on the frontier will score 1, whereas one farm operating beneath the best practice levels is technically inefficient and will score from 0 to 1. Allocative efficiency measures if the input mix selection minimizes costs given a set of output and input price levels. This measure ranges from 0 to 1; with 1 referring to the fully allocative efficiently farm. Allocative and technical efficiency combine to give a measure of overall economic efficiency of the farm which will be referred to as cost efficiency. Scale efficiency measures the effect of the farms' operations size given its output level, input prices, and technology.

Methods to calculate efficiency scores can be grouped into two categories: those that use linear programming techniques to compute a frontier based on the observable data points, mostly some specification of Data Envelopment Analysis (DEA); and those that use econometric techniques to estimate a stochastic non-deterministic frontier function. The latter is called the Stochastic Frontier Approach (SFA). Battese (1992); Bravo-Ureta and Pinheiro (1993); and Thiam, Bravo-Ureta, and Rivas' (2001) used DEA and SFA techniques to study farm efficiency and the causes of farm inefficiencies. The studies can be further divided according to procedures used to obtain efficiency estimates and the manner in which they explain causes of inefficiency. The one-step procedure estimates inefficiency scores and its causes simultaneously, thus taking into account the correlation of efficiency estimates with explanatory factors. Econometric methods are employed in this approach. A two-step economic procedure is used first to estimate efficiency scores and then a Tobit[1] model is used to determine relationship between the efficiency scores and factors that may influence them such as farm size.

The DEA approach benefits from advances in computers to solve sophisticated linear programming problems. Using DEA, no functional form needs to be specified and fitted to the data, which results in both an advantage and a disadvantage. It is an advantage because of the difficulty in estimating functions with the required form (i.e. imposing economic requirements[2] to real data fitting production or cost functions). But, having non statistical foundations, the inefficiency scores obtained cannot be statistically tested; indeed, the DEA estimated scores should be interpreted with care as they only refer to the sample they were calculated from. This method is very sensitive to slacks or extreme observations. DEA studies have been implemented in many fields, including

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[1] Tobit regression is used when the value of the dependent variable is bounded between two numbers. Inefficiency scores range between 0 and 1.

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

banking (Ferrier and Lovell, 1990) government services (Fries and Taci, 2004), and transportation (Piacenza, 2002).

Dhugana et al. (2004) uses a two-step approach to study inefficiency and its causes in a sample of Nepalese rice farms. They use a DEA approach to estimate economic, allocative, technical, and scale efficiencies for one output, multi-input farms in the sample. With five inefficiency scores estimates (EE, AE, TE, PTE, and SE), the authors estimate a Tobit regression to explain the variations in the level of inefficiency between the farms. As factors affecting inefficiency in farms, they include farmer's age, education, gender, and share of non-paid labor. Age (as well as a quadratic age term to measure returns) and education were statistically different from zero at 5 percent confidence level.

Studies that have applied SFA are also numerous in agricultural economics especially, but it has also been applied to other firms or industries (see Puig-Junoy and Ortun, 2004; Linna and Hakkinen, 1995 and 2000). In agricultural economics, SFA is used by both high income and low income countries' studies (see Johnson et al., 1994); to analyze different types of efficiency, their measure and policy implications, such as government programs and subsidies and its effect on technical and allocative efficiency. Battese (1992), and Bravo-Ureta and Pinheiro (1993) list some studies consisting on empirical estimations of efficiency measures using SFA and its application in the agricultural economics area. Thiam, Bravo-Ureta, and Rivas' (2001) compare results from 32 studies on farm technical efficiency to better understand factors of inefficiency. Their research focuses on agriculture from around the world including low to high income countries.

Battese et al. (1989), Kumbhakar et al. (1991) and Battese and Coelli (1995) use a one-approach procedure. These studies have been the foundation for other studies interested in the SFA. In Battese and Coelli (1995), the empirical estimation of a translog production function is applied to 10 cross-sections of data from paddy rice farms in India. Their model is the first one using the one-step procedure approach specifically using panel data. As factors influencing technical efficiency they used operator's age, education, and a time trend. The coefficients in their inefficiency model are all jointly statistically significant; their results suggest that older farmers are more inefficient than young ones, and that there was a decline in inefficiencies in production with time. Puig-Junoy and Argiles (2000) use both a one and two-step procedures in a panel of mixed farms in Spain. Their inefficiency model indicates that farms with a big share of land rented are significantly more inefficient. Hadley et al. (2001) point out the evidence linking production efficiency with financial variables. Their stochastic frontier model results indicate a negative relationship between debt/asset ratios and technical efficiency.

DEA and SFA are different techniques to estimate efficiency measures, both with their merits and disadvantages. Some studies have attempted to compare both approaches (see Sharma et al., 1999; Wadud and White, 2000; Linna and Hakkinen, 1996 and 2000). In general, the estimates differ quantitatively (DEA estimates seem smaller than SFA estimates[3]); however, the order rankings seem to be similar with both methods. It appears that the selection of approach to some extent depends on the specific goals of the study,

[3] See Puig-Junoy and Argiles (2000), p. 14 about commentaries on the comparison of DEA and SFA and the results of their study. 7.

type of data available, and assumptions about the frontier[4] or the assumptions about DEA[5]. Based on previous studies, the variables that have shown to be the most influential to efficiency scores are farm financial variables (such as debt to assets ratio, level of debt), size of the farm, individual farm characteristics (such as age of operator, education, share of non-paid labor, share of land rented, and operator's risk attitude) and technology proxies (such as labor to capital ratio) (Davidova and Latruffe, 2004).

[4] See Coelli, Rao and Battese (1998) for the statistical assumptions made with respect to the form of the function specified, and the distribution of the efficiency scores and the error in SFA.

[5]As noted before, the DEA results always refer to the sample they were estimated from since the frontier is calculated using the own data points. DEA is a deterministic method; the implicit assumption is that all deviations from the frontier are due to inefficiencies, it does not take into account measurement errors or missing variables since it does not calculate a random error component in the estimation of the best practice frontier. See note DEA is a deterministic method; the implicit assumption is that all deviations from the frontier are due to inefficiencies, it does not take into account measurement errors or missing variables since it does not calculate a random error component in the estimation of the best practice frontier. See note For a more detailed explanation on the estimation, varieties and properties of DEA see Charnes, Cooper and Rhodes (1978), Fare, Grosskopf and Lovell (1994), Thiele and Brodersen (1999), and the Steering Committee for the Review of Commonwealth/State Service Provision (1997).

Methodology: DEA and SFA

This paper uses both a DEA and a SFA on 10 years of cross-sectional data on Kansas Farms. We will use the DEA approach to obtain efficiencies scores; and a Tobit regression will be used to analyze the causes of inefficiency. Using the same data, we will model a normalized quadratic cost function and an inefficiency model that will be estimated simultaneously. Thus, we use the two groups of techniques that have been mostly implemented with some degree of variation in their specifications: an econometric technique (SFA), and a non-parametric linear programming one (DEA).

The first one, the parametric stochastic frontier approach (SFA), fit the data to a production or cost function. Then, 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). Production and cost (duality approach) stochastic frontiers are used. Specifications of the functional form vary from Cobb-Douglas to more flexible functional forms such the translog and the quadratic. Models for production and cost functions estimations have been adapted to panel data (Schmidt and Sickles, 1984). Sena (1999) summarizes and compares different software packages in estimating stochastic frontier functions.

Parametric models, specified by a stochastic frontier cost function, were first conceived by Aigner et al. (1977), and expanded in several ways by other authors (Schmidt and. Sickles, 1984; and Battese and Coelli, 1993 and 1995). We use a quadratic cost (and translog cost) function to estimate overall cost efficiency for multi-product Kansas farms over 10 years in the long run, where all inputs are variable. We choose to estimate a cost frontier instead of a production one because we want to measure cost efficiency or overall efficiency. The model used is based on Battese and Coelli (1995), and Coelli et al. (1998), p.202. In a general specification, it can be described as:

$$c_{it} = C\left(y_{it}, w_{it} : \beta\right) + v_{it} + u_{it}$$

where c_{it} are the observed cost of production of firm i, and they are a function of the output quantity, price of inputs, and a vector of parameters β to be estimated. U_{it} is a vector of non-negative cost inefficiency effects, normally assumed to have a half-normal or truncated-normal distribution, that can be formulated to be time-variant or time-invariant. V_{it} is a vector of random errors assumed to be identically and independently distributed, independent of u_{it}. T refers to the year.

The overall efficiency (OE) for the i^{th} firm in a given year can be decomposed into technical and allocative efficiencies. OE is defined as:

$$OE_{it} = exp(-u_{it})$$

Simultaneously, we estimate an inefficiency Tobit model where inefficiency scores are dependant on farm financial and individual characteristics. The cost frontier and the Tobit estimations are performed using maximum likelihood (ML) estimators using the software Frontier 4.1.

DEA is formally defined as "a *linear programming* technique which identifies *best practice* within a sample and measures *efficiency* based on differences between observed and best practice units" (Data Envelopment Analysis ,1997, Glossary, p.). The DEA is a non-parametric technique which uses mathematical programming (Ray, 2001). DEA constructs a non-stochastic production (or cost) frontier over data points, so that some observations lie on or below the frontier (Davidova and Latruffe, 2003)[6].

[6] See note 5 for studies dealing with DEA and its different approaches.

In this study we use an input-oriented multi-output/multi-input DEA approach to a sample of Kansas farm-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 a DEA model under constant return to scale estimated annually for 610 Kansas farms. The DEA problem calculates TE, AE, SE and CE for a sample 610 Kansas farms from 1995 to 2004; this formulation of the DEA problem is called Model 1. Model 1 uses 7 outputs, 10 inputs, and input prices are normalized to 1 in 2004.

The linear programming cost minimization DEA problem is taken from Ferrier and Lovell (1990). It uses input prices to calculate cost efficiency under constant returns to scale for a multi-output and multi-input farm. The DEA linear programming is:

$$\mathit{Minimize}\ \ xjs\ \Sigma w_{js} * x_{js}, \ \text{ sum over } n \text{ for } j=1$$

Subject to:

$$y_i \le \Sigma \mu_s * y_{is}, i = 1,...,m, \ \text{ sum over } S \text{ for } s=1$$

$$x_{js} \ge \Sigma \mu_s * x_{js}, j = 1,...,n, \ \text{ sum over } S \text{ for } s=1$$

$$z_h \le \Sigma \mu_s * z_{hs}, h = 1,...,k_s, \ \text{ sum over } S \text{ for } s=1$$

$$u_s \ge 0, s = 1,...,S,$$

where there are *S* farms, a vector of all farms outputs, y_{is} for m outputs,
a vector of inputs x_{js} for n inputs and w_{js} for input prices, μ_s is an intensity vector that forms convex combinations of observed input and output vectors, and z is the intensity of use of each farm’s technology. To get a full set of efficiency scores, this problem has to be solved for each of the *S* farms in the sample.

The solution is a vector of the optimal/minimum input combinations for the given input prices and output level. Cost efficiency[7] is measured for each farm as the ratio of the optimal cost minimizer vector of inputs for the input price vector, and the actual observed costs. Similar linear programs are specified to calculate technical, allocative and scale efficiency.

Data

The data consist on 10 years cross-section of a sample from the Kansas Farm Management Association (KFMA). There are a total of 610 farms, whose data was collected from 1995 to 2004. We have information on 7 outputs and 10 inputs. Not all the farms produce all model outputs or use all model inputs. The choice of inputs and outputs was made based on their use in farm production and based on results from previous studies.

A summary of the data is available in tables 1 and 2. Most of the farms in this data sample are comprised of commercial farms. The all farms' average gross income is more than $200 Th, the minimum value being $1,600 and the maximum more than a million and a half dollars. Indeed, the average acreage is 1,766; the minimum is 33 acres and the maximum close to 10,000 acres. As for their financial conditions, the mean average debt for all farms all years is close to $ 219,000, the maximum is close to $250,000, and some farms did not have any debt. In terms of working capital, the mean for all the farms all years was more than $100,000.

[7] I need to finish this section, specification of the DEA lp for TE, AE, and SE, and also:

* I want to comment on how the number or inputs/outputs can bias results in DEA problems (Tauer, L.W. and J.J. Hanchar, 1995). Also, in DEA, how sampling variation does influence results, and what is called slacks (outliners) do too.)

Indeed, we would like to make a report of the farms' characteristics between themselves and across years. It is, we want to look at the data from a cross-sectional point of view and a time series one. In the tables section, table 1 shows some variables of interest by year, i.e. gross annual income, annual working capital, and annual total debt. It shows that the size and financial variables per farm across years are subject to little variability. Maxima and minima values for each variable are close across years; the mean value is also quite constant across years, being around $250,000 the mean annual debt carried by farms.

In Figures 1, 2, 3, and 4 we compare the 610 farms to each other. We have picked the year 1995 for no reason, but as an example. Figures 1, 2, 3, and 4, look at farm's size by gross income, by total acreage, by debt level, and by working capital respectively. As we said, most farms can be considered commercial farms; the majority of them have between 1,000 and 2,000 total annual acres. An average of each farm over the 10 years sample helps us categorize farms into 4 classes according to size (i.e. gross income). Out of a total of 610 farms, 46% of farms in the sample have an annual average gross income between $250-100 Th, that is, the majority of farms belong to category 3. The number for farms in category 2 and 4 is quite similar, with close to 23% and 24.5% of farms in these categories respectively. Only 6.5% of farms in the sample belong to the first category. Average gross incomes per category, as well as the number of farms per category are summarized in the chart below:

Category (in terms of Gross Income)	**1** More than $.5M	**2** $500-250 Th	**3** $250-100 Th	**4** Less than $100 Th
Number	40	140	281	149
Aver. Gross	732,182	345,030	165,822	67,005

References

Aigner, D., K. Lovell and P. Schmidt. (1977). "Formulation and estimation of stochastic production function models", *J. of Econometrics,* 6, 21-37.

Battese, G.E.(1992) Frontier Production Functions and Technical Efficiency: A Survey of Empirical Applications in Agricultural Economics, *Agricultural Economics*, 7, 185-208

Battese, G.E. and T.J. Coelli (1992) Frontier production functions: Technical Efficiency and Panel Data: With Application to Paddy Farmers in India, *J. of Productivity Analysis*, 3, 153-169

Battese, G.E. and T.J. Coelli (1995) A Model for Technical Efficiency Effects in a Stochastic Frontier Production Function for Panel Data, *Empirical Econ.*, 3, 153-169

Bierlen R., and A. M. Featherstone. (1998) Fundamental q, Cash Flow, and Investment: Evidence from Farm Panel Data, *Rev. of Econ. and Stat.*, 80, 427-435

Bravo-Ureta, B.E., and A.E. Pinheiro. (1993) Efficiency Analysis of Developing Country Agriculture: A Review of the Frontier Function Literature. *Agri. and Resource Econ. Review,* 22, 88-101.

Casu, B. and C. Girardone (2002) Efficiency in Large Banks in the Single European Market, Working Paper, Middlesex U. Business School, Dept. of Economics, London

Chavas, J.P., and M. Aliber (1993) An Analysis of Economic Efficiency in Agriculture: A Non-Parametric Approach. *J. of Agr. And Resource Econ.*, 18, 1-16

Charnes, Cooper, and Rhodes (1978) Measuring the Efficiency of Decision Making Units”. *European J. Operations Research*, 429-44

Coelli, T.J. (1995) Recent Developments in Frontier Modeling and Efficiency Measurement, *Australian J. of Agri. Econ.*, 39, 219-245

Coelli, T.J., and G.E. Battese (1996) Identification of Factors which Influence the Technical Inefficiency of Indian Farmers, Australian *J. of Agri. Econ.*, 40, 103-128

Coelli, T.J., D.S.P. Rao and G.E. Battese (1998) An Introduction to Efficiency and Productivity Analysis, Kluwer Academic Publishers, Boston, US

Davinova S.,and L. Latruffe (2003) Technical Efficiency and Farm Financial Management in Countries in Transition, Working Paper, INRA, France

Dhungana, B.R., P.L. Nuthall, and G.V. Nartea, (2004) Measuring the Economic Inefficiency of Nepalese Rice Farms Using Data Envelopment Analysis, *Australian J. of Agr. and Resource Econ.*, 48 (2), 347-369

Kumbhakar S.C., and C.A.K. Lovell, (2000) Stochastic Frontier Analysis, Cambridge University Press

Fare, R., S. Crosskopf and H. Lee (1990) Nonparametric Approach to Expenditure-Constraint Profit Maximization. *Amer. .J. Agr. Econ.*, **72**, 574-81

Ferrier, G.D., C. A. Lovell, (1990) Measuring Cost Efficiency in Banking: Econometric and Linear Programming Evidence, *J. of Econometrics*, 46, 229-245

Fries, S., and A. Taci, (2004) Cost Efficiency of Banks in Transition: Evidence from 289 Banks in 15 Post-Communist Countries. Working Paper, European Bank for Reconstruction and Development, London

Girardone C. (2000), *An Analysis of the Determinants of Bank Efficiency. The Case of Italian Banks*, PhD Thesis, University of Wales Bangor.

Handley D., B Shankar, C. Thirtle, and T. Coelli (2003) Financial Exposure and Farm Efficiency: Evidence from the England and Wales Dairy Sector, Paper Presented at the annual meetings of the American Agricultural Association, Chicago, August 5-8 2001. Draft, please quote only with permission. Contact: Bhavani Shankar (b.shankar@reading.ac.uk)

Johnson, S.R., A. Bouzaher, A. Carriquiry, H. Jensen, and P.G. Lakshminarayan (1994) Production Efficiency and Agricultural Reform in Ukraine, *Amer. J. Agr. Econ.*, 76(3), 629-635

Linna, M., and U. Hakkinen (2000) Determinants of Cost Efficiency of Finnish Hospitals: A Comparison of DEA and SFA,

Linna, M. and U. Häkkinen. (1996). A comparative Application of Econometric Frontier and DEA Methods for Assessing Cost Efficiency of Finnish hospitals." accepted for publication.

Paul, C.J.M., W.T. Johnston, and G.A.G. Frengley (2000) Efficiency of New Zealand Sheep and Beef Farming: the impacts of regulatory reform, *Rev. of Econ. and Stat.*, 82, 325-36

Piacenza, M. (2002) Regulatory Contract and Cost Efficiency: Evidence from the Italian Local Public Transport, CERIS, Hermes

Puig-Junoy, J., and J.M. Argiles (2000) Measuring and Explaining Farm Inefficiency in a Panel Data Set of Mixed Farms, Dept. of Econ. And Bus., Pompeu Fabra University, Working Paper, Barcelona, Spain

Puig-Junoy, J., and V. Ortun (2004) Cost Efficiency in Primary Care Contracting: A Stochastic Frontier Cost Function Approach, *Health Econ*., 13, 1149-65. Published online in Wiley InterScience at www.interscience.wiley.com

Ray, S.C. (2004) Data Envelopment Analysis: Theory and Techniques for Economics and Operational Research, Cambridge University Press

Schmidt, P., and R.C. Sickles (1984) Production Frontiers and Panel Data, *J. of Bus. and Econ. Statistics*, **2**(4), 367-374

Sena, V. (1999) Stochastic Frontier Estimation: A Review of the Software Options, *J. of Applied Econometrics*, 14(5), 579-586

Sharma, K.R., P. Leung, and H.M. Zaleski (1999) Technical, Allocative and Economic Efficiencies in Swine Production in Hawaii: A Comparison of Parametric and Nonparametric Approaches, *Agr. Econ*., 20, 23-35

Tauer, L.W. and J.J. Hanchar (1995) Nonparemetric Technical Efficiency with K Firms, N. Inputs, and M Outputs: A Simulation. *Agri. and Resource Econ. Review*, 24, 185-89

Thiam, A., B.E. Bravo Ureta, and T.E. Rivas (2001) Technical Efficiency in Developing Country Agriculture: A Meta-Analysis. *Agr. Econ*., 25**,** 235-43

Varian, H.R. Goodness-of-Fit in Optimizing Models. *J. Econometrics*, 46, 125-40

Wadud, A. and B. White (2000) Farm Household Efficiency in Bangladesh: A Comparison of Stochastic Frontier and DEA Methods, *Applied Econ*., 32, 16665-73

Table 1. Kansas Farm Financial and Size Data

Average Values (all farms, 1995 - 2004)	Obs.	Mean	Std. Dev.	Min	Max
Farm Characteristics					
Number of units (DMU)/ Farms	6100			1	610
Year	6100			95	104
Gross Farm Income ($)	6100	219,953	195,328	1,600	1,697,348
Total Acres	6100	1,766	1,228	33	9,573
Aver. Total Assets ($)	6100	752,996	582,075	40,587	7,011,334
Aver. Total Debt ($)	6100	218,960	257,929	0	2,447,343
Aver. Current Assets ($)	6100	187,696	189,444	116	1,671,815
Aver. Current Debt ($)	6100	87,125	141,669	0	1,266,217
Outputs					
Small Grain Prod. (Bu)	6100	10,493	13,594	0	138,242
Feed Grain Prod. (Bu)	6100	18,984	27,543	0	245,589
Oilseed Prod. (Bu)	6100	5,767	9,073	0	114,100
Hay and Forage Prod. (Tons)	6100	92	239	0	4,639
Beef Prod. (Pounds)	6100	67,731	124,717	0	1,685,488
Dairy Prod. (Pounds)	6100	143,848	629,768	0	7,029,769
Miscellaneous ($)	6100	14,871	32,066	0	574,564

Table 1. Continued					
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
Other Farm Variables					
Working Capital ($)	6100	100,571	167,861	-805,171	1,671,787
Aver. Total Debt ($)	6100	218,960	257,929	0	2,447,343

Table 2. Kansas Farm Financial and Size Data per Year, 1995 – 2004

Year	Variable	Mean	Std. Dev.	Min.	Max.
	Farms	NA	NA	1	610
2004					
	Annual Total Average Debt	225,208	271,373	0	1,969,436
	Annual Average Working Capital	105,141	173,452	-604,881	1,338,093
	Gross Annual Income	247,145	225,756	1,600	1,645,111
	Total Acreage	1,785	1,257	33	9,537
2003					
	Annual Total Average Debt	227,245	272,049	0	2,101,526
	Annual Average Working Capital	89,085	170,423	-805,171	1,367,096
	Gross Annual Income	227,259	205,082	15,026	1,402,541
	Total Acreage	1,833	1,257	88	9,573
2002					
	Annual Total Average Debt	227,255	273,248	0	2,282,377
	Annual Average Working Capital	86,919	168,769	-557,236	1,402,777
	Gross Annual Income	202,151	182,783	11,244	1,240,767
	Total Acreage	1,831	1,280	80	9,548
2001					
	Annual Total Average Debt	221,947	267,920	0	2,421,141
	Annual Average Working Capital	93,660	166,007	-523,304	1,376,078
	Gross Annual Income	196,866	175,616	5,570	1,122,421
	Total Acreage	1,795	1,222	138	8,283

Table 2. Continued.

1999					
	Annual Total Average Debt	221,771	257,958	0	2,238,152
	Annual Average Working Capital	102,865	162,144	-497,778	1,440,738
	Gross Annual Income	194,500	174,482	6,359	1,404,967
	Total Acreage	1,761	1,238	117	8,683
1998					
	Annual Total Average Debt	220,545	256,883	0	2,368,763
	Annual Average Working Capital	116,514	173,609	-525,359	1,671,787
	Gross Annual Income	198,571	165,834	10,674	1,246,096
	Total Acreage	1,732	1,203	164	8,637
1997					
	Annual Total Average Debt	210,915	246,882	0	2,447,343
	Annual Average Working Capital	123,233	177,439	-473,826	1,660,708
	Gross Annual Income	273,483	215,586	10,069	1,542,546
	Total Acreage	1,751	1,233	185	9,541
1996					
	Annual Total Average Debt	206,258	235,384	0	2,344,175
	Annual Average Working Capital	99,761	163,367	-555,560	1,432,323
	Gross Annual Income	258,041	227,555	4,478	1,697,348
	Total Acreage	1,698	1,161	152	8,327

Table 2. Continued.

1995				
Annual Total Average Debt	209,060	234,912	0	2,338,757
Annual Average Working Capital	89,085	158,299	-712,151	1,201,590
Gross Annual Income	210,266	180,284	7,469	1,562,863
Total Acreage	1,696	1,190	151	8,554

Table 3. Efficiency Scores for Data Envelopment Analysis (DEA), 1995-2004

	Type of Efficiency	DEA Efficiency Scores
1995	Technical Efficiency	0.9499
	Allocative Efficiency	0.7608
	Scale Efficiency	0.8875
	Cost Efficiency	0.6463
1996	Technical Efficiency	0.9454
	Allocative Efficiency	0.7728
	Scale Efficiency	0.8721
	Cost Efficiency	0.6401
1997	Technical Efficiency	0.9418
	Allocative Efficiency	0.7824
	Scale Efficiency	0.8934
	Cost Efficiency	0.6647
1998	Technical Efficiency	0.9543
	Allocative Efficiency	0.8161
	Scale Efficiency	0.8985
	Cost Efficiency	0.7032
1999	Technical Efficiency	0.9427
	Allocative Efficiency	0.7671
	Scale Efficiency	0.8667
	Cost Efficiency	0.6317

Table 3. Continued

	Type of Efficiency	DEA Efficiency Scores
2000	Technical Efficiency	N/A
	Allocative Efficiency	N/A
	Scale Efficiency	N/A
	Cost Efficiency	N/A
2001	Technical Efficiency	0.9642
	Allocative Efficiency	0.8052
	Scale Efficiency	0.8867
	Cost Efficiency	0.6905
2002	Technical Efficiency	0.9524
	Allocative Efficiency	0.8091
	Scale Efficiency	0.8924
	Cost Efficiency	0.6913
2003	Technical Efficiency	0.9645
	Allocative Efficiency	0.8221
	Scale Efficiency	0.8718
	Cost Efficiency	0.6933
2004	Technical Efficiency	0.9518
	Allocative Efficiency	0.8000
	Scale Efficiency	0.8817
	Cost Efficiency	0.6760

Figure 1. Farms by Gross Income in Percentage Units in 1995

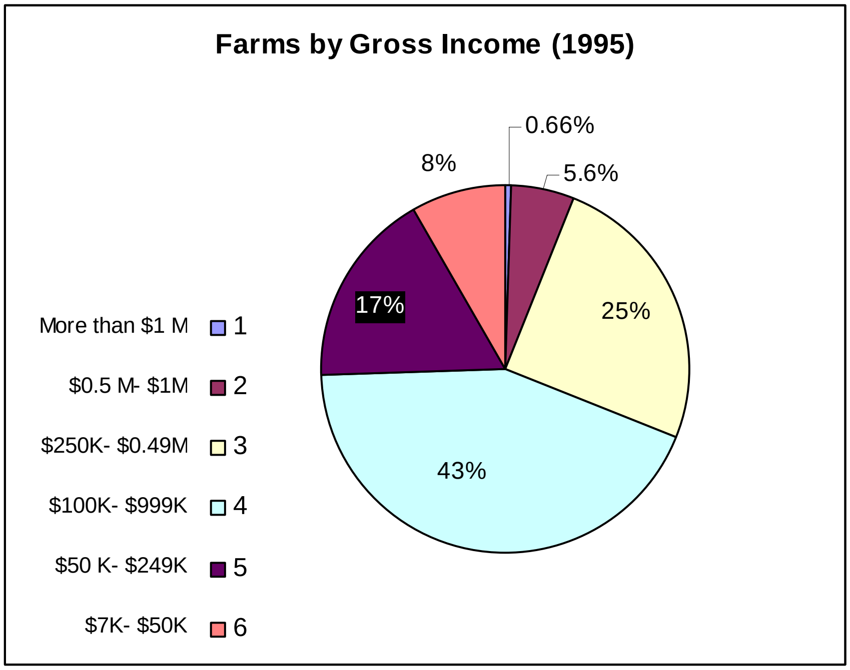

Figure 2. Farms' by Total acreage in Percentage Units in 1995

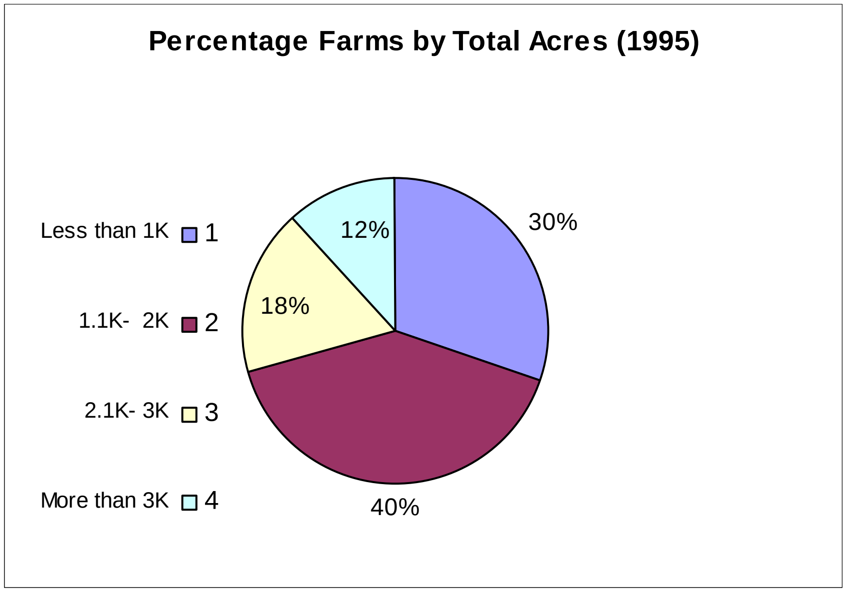

Figure 3. Farms' by Annual Average Total Debt in Percentage Units in 1995

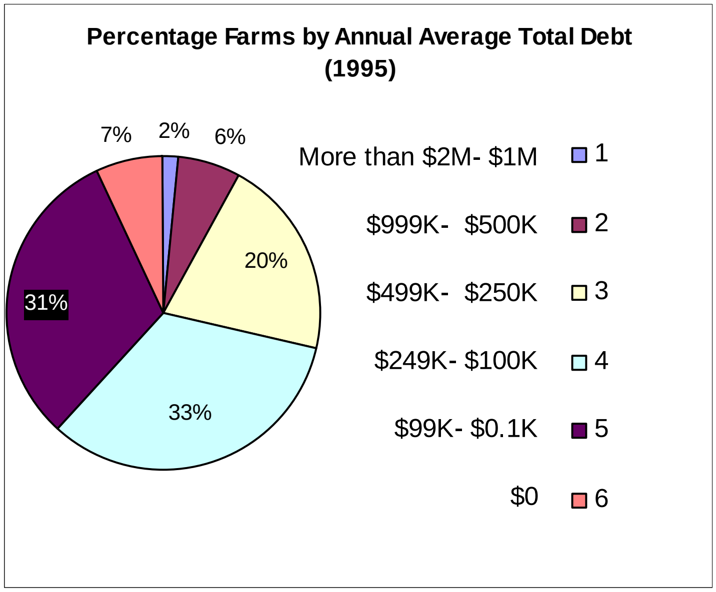

Figure 4. Farms' by Working Capital in 1995