EVALUATION OF NORTH DAKOTA FARM PRODUCTION EFFICIENCY AND FINANCIAL PERFORMANCE OVER TIME

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ABSTRACT

Bayda, Volodymyr Volodymyrovich; M.S.; Department of Agribusiness and Applied Economics; College of Agriculture, Food Systems, and Natural Resources; North Dakota State University; May 2003. Evaluation of North Dakota Farm Production Efficiency and Financial Performance Over Time. Major Professor: Dr. David K. Lambert.

Farm-level efficiency and productivity measures are derived using Data Envelopment Analysis and Malmquist Total Factor Productivity (TFP) indexes for panel data of 130 North Dakota farms over 7 years. On average, the farms in the sample were 0.75 technically efficient and 0.96 scale efficient. Over the 1995-2001 period, the farms experienced a modest productivity growth of approximately 1.7% per year. Most of the increase was attributed to technical change, while changes in technical efficiency had very small effects on the Malmquist TFP.

Estimated technical efficiency (TE) scores are used in a regression analysis to reveal the relationship between the efficiency measures and different farm characteristics. TE is influenced by regional and time effects as well as by farm type. TE is positively influenced by farm size as measured in terms of accrual gross income and also positively influenced by the long-term debt-to-asset ratio. Part-time farmers are found to be less efficient in allocating their farm resources as compared to full-time farmers. Insurance payments and current debt-to-asset ratio negatively affect TE, while no statistically significant relationship is found between TE and the following factors: intermediate debt-to-asset ratio, farming experience, and government payments.

Strong and positive relationships between returns on assets (ROA) and technical and scale efficiencies and ROA and Malmquist TFP indexes indicate that farm financial performance is largely dependent upon a producer's ability of staying on the production frontier and adopting new technology.

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V.V.B.

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CHAPTER I. INTRODUCTION

Measuring farm production efficiency and productivity growth has a long history in agricultural production analysis. Results of such comparative analyses indicate differences in efficiency and productivity among producers and how efficiency may change over time. The results are also used to identify the impact of different factors (such as farm size, producer's education, experience, additional employment outside of the farm, and insurance and government payments) on production efficiency, how farm profitability is related to efficiency and productivity growth, and to identify economies of scale and scope. Results are extensively used by governmental agencies to identify trends in productivity and to determine how farm policies influence different farm groups.

Production efficiency and productivity have been measured using parametric and nonparametric approaches. Parametric approaches assume a functional approximation to the underlying technology and econometrically derive parameter estimates for the model. Nonparametric approaches, proposed by Fare et al. (1985), do not impose parametric restrictions on the underlying technology. The level of optimal farm performance under such approaches is determined by constructing an efficiency frontier, which consists of the best performing farms in the industry, and by analyzing the relationship of individual farms to that frontier.

A short-term random fluctuation in production by a firm may impact the estimation of efficiency and productivity change. However, those fluctuations may not be related to efficiency and productivity change. Thus, a few years of observations are necessary in order to erase annual random effects and estimate actual farm efficiency and productivity (Fraser and Hone, 2001).

In this thesis, farm-level technical and scale efficiencies and productivity changes will be estimated employing Data Envelopment Analysis (DEA) for a sample of North Dakota farms using a panel data set of 130 farms over a 7-year time period, from 1995 to 2001. Efficiency scores will be calculated for each farm in the data set on an annual basis. The efficiency measures form the basis for estimating changes in farm productivity using Malmquist Total Factor Productivity (TFP) indexes. The effect of changes in production efficiency on the productivity growth of individual farms can then be determined.

Objectives

The overall goal of this thesis is to estimate productivity growth and technical and scale efficiency for a selection of North Dakota farms, to examine which factors play an important role in determining farm technical efficiency, and to identify whether there is a relationship between a farm's financial performance and production efficiency and productivity growth. The following objectives are identified:

1) To develop and employ a model that will allow assessing relative technical and scale efficiencies of selected farms year by year;
2) To identify sources of inefficiency and rank them by the level of influence;
3) To measure farm productivity growth over time;
4) To estimate the level of impact that individual components, such as changes in pure technical efficiency, scale efficiency, and technical change (technical progress or regress), have on productivity growth; and

5) To analyze how profitability of individual farms is related to their technical and scale efficiency and to determine if changes in farm productivity have an impact on a farm's financial performance.

Hypotheses

The following hypotheses will be examined in the thesis:

1) There is moderate productivity growth of approximately 1-2% in farm production practices over time, which is mostly attributed to technical change. This hypothesis is supported by the results of several studies (Ball et al., 1997; Zofio and Lovell, 2001) which found that the average annual rate of productivity growth since 1948 for US farms was around 2%.
2) The variation in technical efficiency indexes is considerable (about 25-35%) among farms. Economies of scale have substantial impacts on economic efficiency. This hypothesis is supported by the following statistical information. The number of farms in North Dakota has steadily declined since 1930. In 1997, there were 30,504 farms, which are about 20,000 farms less than in 1964. The average size of farms has increased from 875 acres to almost 1,300 acres. Analysis of trends in different sized farms shows that while very small farms in North Dakota (less than 180 acres) and very large farms (2,000 acres and above) are generally increasing or staying steady in terms of numbers, medium farms (180-1,999 acres) are decreasing (USDA, 1998). A consistently decreasing number of farms, mostly those of medium size, suggests that inefficient farms are forced out of business, while enlargement of remaining farms suggests economies of scale in the industry. The

upward trend in small farms can be explained by the fact that these are mostly "hobby" farms, which provide only supplemental income to the owners and "preserve the lifestyle of the past" (USDA, 1998).

3) Farm-specific factors, such as farmer's experience and age, education level, farm size, and land tenure, affect a farm's technical efficiency. The results of several studies about the influence of farm-specific factors on farm economic performance are mixed: sometimes an effect was found, but sometimes it was not. Even when an effect was found, the sign of the impact on efficiency differed between studies (Rougoor et al., 1998). Findings of those studies might lead to the conclusion that results are dependent upon the farms' geographical location and specialization.
4) There is a strong positive relationship between a farm's technical and scale efficiency and financial performance. Economically efficient farms should also have better financial measures.
5) There is a strong positive relationship between a farm's productivity and financial performance. Increases in a farm's productivity over time as compared to its peers should make that farm better off financially as well.

Procedures and Methodology

Data for conducting the research are obtained from the North Dakota Farm and Ranch Business Management Education program data set. This data set consists of three major categories: whole farm financial reports, crop reports, and livestock reports. The reports contain information from more than 500 farms each year, from 1989 to 2001. However, only farms that participated in the program for seven consecutive years from

1995 to 2001 and submitted all necessary information are used for the analysis. There are 130 such farms.

A DEA output-oriented model is employed to measure pure technical and scale efficiencies for each farm in the data set. Resulting estimates of farm technical efficiency scores are regressed against a variety of farm-specific descriptive variables in order to determine the importance of those different factors in explaining efficiency levels and changes in a farms' technical efficiency.

The Malmquist productivity index, theoretically derived by Caves et al. (1982a), is calculated using Fare et al.'s (1989, 1994b) procedure to assess farm productivity growth and its components: technical change and changes in pure technical and scale efficiencies.

An additional econometric analysis is implemented to find a relationship between farm financial measures of performance (ROA) and measures of farm technical and scale efficiencies, as well as between-farm financial measures of performance (ROA) and Malmquist indexes, in order to investigate the effects of farm productivity changes over time on a farm's financial situation.

Organization

Chapter II provides an overview of the existing literature on productivity growth, production efficiency and measurement, and a discussion of inputs and outputs used in different studies in order to assess efficiency and productivity measures. Chapter III describes methods used to perform an analysis of technical and scale efficiency and technological change of selected farms in North Dakota and to estimate the impacts of efficiency and productivity measures on financial performance. Chapter III also contains the description of the data used in the analysis. Results are presented in Chapter IV. Chapter V includes thesis conclusions and limitations and an outline of needs for future research.

CHAPTER II. LITERATURE REVIEW

Introduction

The literature review focuses on different approaches to measure firm economic efficiency and productivity growth. First, efficiency and productivity growth as well as their components are defined. Second, nonparametric and econometric approaches to measure firm efficiency and productivity growth are discussed. Finally, a literature review of the factors that affect efficiency is presented.

Economic Efficiency

Lovell (1993) relates the efficiency of the firm to a comparison between observed and optimal values of its outputs and inputs. If the optimum is defined in terms of production possibilities, the resulting comparison measures technical efficiency. If the optimum is defined in terms of behavioral goals of the firm (e.g., profit or revenue maximization and cost minimization), then efficiency is economic and is measured by comparing a firm's observed and optimum achievement of goals (e.g., profit, revenue, and cost) subject to the appropriate consideration of technology and prices.

Farrell (1957) proposed that the economic efficiency of a firm consists of two components: technical (or physical) efficiency and allocative (or price) efficiency. Technical efficiency refers to the ability of a firm to produce maximal potential output from a given amount of input or to use a minimal amount of inputs in order to produce a given amount of output. Thus, technical efficiency depicts the ability of a firm to produce on the production frontier. Koopmans (1951) provided a formal definition of technical efficiency: a producer is technically efficient if an increase in any output requires a reduction in at least one other output, and if a reduction in any input requires an increase in at least one other input or a reduction in at least one output.

Debreu (1951) and Farrell (1957) introduced a measure of technical efficiency. This measure is defined as one minus the maximum equiproportionate reduction in all inputs that still allows continued production of given outputs. A score of unity means a firm is technically efficient since no equiproportionate input reduction is feasible, and a score less than unity indicates the extent of a firm's technical inefficiency.

Satisfying several properties,[1] the Debreu-Farrell measure of technical efficiency is widely applied. However, as noted by Lovell (1993), it does not coincide with Koopman's definition of technical efficiency. Koopman's definition is stringent: it requires simultaneous membership in both efficient subsets, while the Debreu-Farrell measure only requires presence on the efficiency isoquant (Lovell, 1993). Thus, if any producer is located on the isoquant outside of the efficient subset, the Debreu-Farrell measure identifies him as efficient, although he is not following Koopman's more stringent definition.

The significance of the problem depends on the number of observations that lie on the isoquant outside of the relevant efficient subset. The problem can be avoided in econometric analysis, which imposes equality between efficiency isoquants and efficient subsets. The problem may be important in the nonparametric approach, where non-zero input and output slacks may coincide with a technical efficiency measure of one. Here, slack variables represent the amounts of not-produced output or overused inputs. If the

[1] 1). Debreu-Farrell input-oriented measure of technical efficiency ($DF_i(y,x)$) is homogeneous of degree – 1 in inputs, and Debreu-Farrell output-oriented measure of technical efficiency ($DF_o(y,x)$) is homogeneous of degree + 1 in outputs.
2). $DF_i(y,x)$ is weakly monotonically decreasing in inputs, and $DF_o(y,x)$ is weakly monotonically decreasing in outputs.
3). $DF_i(y,x)$ and $DF_o(y,x)$ are invariant with respect to changes in units of measurement (Shephard, 1970).

problem appears to be significant in conducting research, then one may report Debreu-Farrell technical efficiency scores as well as slack variables side by side for each observation, which will enable elimination of inefficient firms with a technical efficiency score of one and non-zero slacks from the efficient ones with zero slacks (Lovell, 1993).

Allocative efficiency represents the ability of a firm to utilize the cost-minimizing input ratios or revenue-maximizing output ratios. Allocative inefficiency occurs if the ratio of marginal physical products of two inputs does not equal the ratio of their prices, e.g., $f_j / f_i \neq w_j / w_i$, where f_i is a marginal physical product of the input x_i, and w_i is the price of the input x_i (Bailey et al., 1989). Therefore, a firm is allocatively efficient if it uses the optimal combination of inputs with respect to their prices. Similarly, first-order conditions from revenue maximization can be used to determine optimal output ratios based on output prices and marginal costs.

The economic efficiency of the firm is the product of technical and allocative efficiency. Hence, in order to be economically efficient, a firm must be both technically and allocatively efficient.

If the analyzed industry exhibits variable returns-to-scale, then another component of economic efficiency, scale efficiency, is present. Scale efficiency is used to determine how close an observed firm is to the most productive scale size (Forsund and Hjalmarsson, 1979; Banker and Thrall, 1992). A firm may be scale inefficient if it exceeds the most productive scale size (therefore experiencing decreasing returns-to-scale) or if it is smaller than the most productive scale size (therefore failing to take full advantage of increasing returns-to-scale). Scale inefficiency for a firm is defined with respect to those firms in the sample which operate where average and marginal products are equal (Forsund et al., 1980).

The analyzed industry might also exhibit economies of scope. In this case, scope efficiency exists. Scope efficiency relates to benefits realized by firms that produce several product lines compared to specialized enterprises. This aspect of economic efficiency is of particular interest in agriculture since there are many debates on optimal production structure of agricultural enterprises. An empirical measurement of farms' scope efficiency was proposed by Chavas and Aliber (1993). They measured scope efficiency as the relative cost of producing livestock and crops separately compared to their joint production.

Approaches to Efficiency Measurement

Empirical analysis in production economics has been dominated by estimators derived under symmetric error assumptions, rather than enveloping the data from above, as would be appropriate for a production or profit function, or from below, as would be appropriate for the cost function (Coelli, 1995). Assuming a central tendency in observed firms, the estimated functions represent the shape of technology of an average firm (Lovell, 1993). Conversely, the frontier approach, which has become increasingly popular over the last ten years, provides a measure of technology represented by the best-performing firms of the industry. The performance of all firms is compared against a constructed frontier, which enables the analyst to evaluate each firm's behavior (Charnes et al., 1997).

A frontier function represents a best-practice technology, against which the efficiency of the firms within the industry can be measured (Coelli, 1995). If a firm belongs to the frontier, it is efficient. If a firm is beneath the efficiency frontier, then it is inefficient and further analysis identifies the sources and extent of the inefficiency.

There are two primary frontier approaches to the measurement of efficiency: parametric, which involves econometric methods, and nonparametric, which employs mathematical programming. The parametric approach relies on a parametric specification of the production function, cost function, or profit function fitted to the data (e.g., Forsund et al., 1980; Bauer, 1990a).

Parametric specification of the production function is mostly performed by employment of stochastic frontier analysis (SFA), which accounts for both inefficiency and random noise effects. Given the fact that production processes in agriculture are stochastic, the choice of SFA for efficiency measurement seems obvious. However, an important weakness of the SFA is that parametric restrictions on the production technology can confound the efficiency results (Lovell, 1993; Reinhard et al., 1999; Bauer, 1990b).

The non-parametric Data Envelopment Analysis (DEA) approach for measuring efficiency was introduced in 1978 by Charnes, Cooper, and Rhodes. They used mathematical programming to generalize Farrell's (1957) single-output/single-input technical efficiency measure by transforming a multiple-output/multiple-input technology into one combined output and one combined input. This technique has become an accepted management science tool in performing efficiency analysis. Charnes et al. (1978) described the DEA methodology as a "mathematical programming model applied to the observed data (which) provides a new way of obtaining empirical estimates of extremal relations such as the production functions and/or efficiency production possibility surfaces that are the cornerstones of modern economics" (p. 432). The increasing popularity of this approach is endorsed by the fact that between 1978 and 1992, over 400 articles, books, and dissertations involving DEA were published (Charnes et al., 1997).

Contrary to econometric approaches, programming approaches avoid the problem of misspecification of functional form (of both technology and inefficiency). Also, programming approaches can easily handle disaggregated inputs and multiple output technologies (Charnes et al., 1997). The latter property is especially desirable in this study.

However, being non-stochastic, the DEA approach does not distinguish data noise and inefficiency (Lovell, 1993; Coelli, 1995). It should be noted here that stochastic DEA models, which eliminate such problems, have been developed in the literature (e.g., Land et al., 1990; Desai and Schinnar, 1987; Sengupta, 1987; Petersen and Olesen, 1989). However, empirical implications of these models are extremely difficult due to rigorous data requirements. In addition to the inputs and outputs data, it is necessary to have information on expected values of all variables, variance-covariance matrices for all variables, and probability levels at which feasibility constraints are to be satisfied (Lovell, 1993).

Another problem that might occur with use of DEA models refers to the dimensionality of the input/output space relative to the number of observations in the cross-section. The dimensionality problem arises when the number of observations is relatively small compared with the number of inputs and outputs used (Suhariyanto, 2000). A negative consequence of this problem is that many of the analyzed DMUs will be rated as "efficient" and therefore lie on the production frontier (Leibenstein and Maital, 1992).

There are different opinions about the ratio between the number of observations and number of inputs and outputs that will enable the DEA model to discriminate efficient firms from inefficient. Charnes and Cooper (1990) stated that ratio should equal at least three, while Fernandez-Cornejo (1994) argued that it should exceed five. Smith (1997), after conducting a simulation study, found that even in cases when the number of observations exceeded the number of factors by more than thirteen times, DEA still can overestimate true efficiency by 27 percent.

DEA Models

There are four basic models in DEA: (1) additive; (2) multiplicative; (3) Charnes, Cooper, and Rhodes (CCR); and (4) Banker, Charnes, and Cooper (BCC). A selection of a particular model for an analysis is based on implicit assumptions about the geometry of the envelopment surface, returns-to-scale, and orientation (Charnes et al., 1997).

Models that utilize additive combinations of inputs and outputs yield a piecewise linear envelopment surface, while multiplicative combinations of inputs and outputs result in piecewise Cobb-Douglas or piecewise log-linear envelopment surfaces. Implicit assumptions about returns-to-scale yield either variable returns-to-scale (VRS) or constant returns-to-scale (CRS) envelopment surfaces.

Furthermore, selection of a model's orientation determines the path of inefficient DMUs to the efficient frontier. In non-oriented models, output slack and input excess are considered comparable in that neither should preempt or receive greater scrutiny than the other, while in oriented models, either inputs or outputs preempt the other in that proportional movement toward the frontier is first achieved in input or output space, respectively (Ali and Seiford, 1993). Thus, in an output orientation model, the objective is to produce the maximum amount of outputs with a given set of inputs, so the efficiency frontier is constructed via proportional augmentation of all outputs. In an input orientation model, the objective is to produce desired output with a minimum of inputs; therefore, the efficiency frontier is constructed via proportional reduction in all inputs. Under constant returns-to-scale, the measure of input efficiency will be the inverse of the measure of output efficiency (Fare and Lovell, 1978).

Although efficiency scores are going to be different for the same DMUs under each model, a DMU is characterized as inefficient in one of the models if and only if it is characterized as inefficient by the other models as well (Ahn et al., 1988). The only exception to this statement is the CCR model, under which a firm can be inefficient while being efficient under all other models. Features of all of the models are summarized in Table 2.1.

Empirical Comparison of DEA and Stochastic Frontier Models

Coelli (1995) presented a review of both parametric and non-parametric techniques used in efficiency measurement, including their limitations, strengths, and applications in agricultural production. Although his review indicated that parametric approaches were used more frequently then DEA, neither model appears to have dominant advantages above the other.

Sharma et al. (1999) compared parametric and non-parametric approaches under both CRS and VRS assumptions to efficiency measurement in swine production in Hawaii. Results indicated that the efficiency rankings of the analyzed producers based on both approaches were highly correlated. However, overall results obtained from DEA were found more robust than those from the econometric approach. The output variable in the

Table 2.1. Comparison of Basic DEA Models

Model	*Returns-to-Scale*	*Envelopment Surface*	*Projection Map*	*Envelopment Metric (Range)*	*Units Invariant*	*Involves Non-Archimedian*
Additive	Variable	Piecewise Linear	$Y_0 \to Y_0 + S^+$ $X_0 \to X_0 - S^-$	L1 ($z \leq 0$)	No	No
Invariant Multiplicative	Variable (Log-Linear)	Piecewise Cobb-Douglas	$Y_0 \to Y_0 e^{s^+}$ $X_0 \to X_0 e^{-s^-}$	e^{L1} ($e^{s+} \geq 1, 0 < e^{s-} \leq 1$)	Yes	No
Variant Multiplicative	Constant (Log-Linear)	Piecewise Log-Linear	$Y_0 \to Y_0 e^{s^+}$ $X_0 \to X_0 e^{-s^-}$	e^{L1} ($e^{s+} \geq 1, 0 < e^{s-} \leq 1$)	No	No
BCC Input	Variable	Piecewise Linear	$Y_0 \to Y_0 + s^+$ $X_0 \to \Theta X_0 - s^-$	Radial (Inputs) ($0 < \Theta < 1$)	Yes	Yes
BCC Output	Variable	Piecewise Linear	$Y_0 \to \phi Y_0 + s^+$ $X_0 \to X_0 - s^-$	Radial (Outputs) ($\phi \geq 1$)	Yes	Yes
CCR Input	Piecewise Constant	Piecewise Linear	$Y_0 \to Y_0 + s^+$ $X_0 \to \Theta X_0 - s^-$	Radial (Inputs) ($0 < \Theta < 1$)	Yes	Yes
CCR Output	Piecewise Constant	Piecewise Linear	$Y_0 \to \phi Y_0 + s^+$ $X_0 \to X_0 - s^-$	Radial (Outputs) ($\phi \geq 1$)	Yes	Yes

Source: Charnes et al. (1997)

study was a weighted output of live pigs produced (in tons) during 1994. The inputs included feed, in tons; labor, in person days; other variable inputs, in dollar value; and fixed input, which incorporated the total cost of fixed inputs including insurance, taxes, and depreciation (in dollar value). Farm-specific factors used to analyze their influence on economic efficiency and its components included farm size, farmer's education level, farmer's experience, farm location, types of pigs produced (market or feeder), and feeding regime (mixed or grain feeding). Farm size, experience, education level, and types of pigs produced were found significant in influencing economic efficiency. Farm location was significant in determining scale inefficiency.

Wadud and White (2000) compared DEA (both VRS and CRS) and stochastic frontier methods while estimating farm household efficiency of rice farmers in two villages in Bangladesh. Mean technical efficiency obtained from the stochastic frontier was 0.7913 and from CRS and VRS DEA, 0.7890 and 0.8580, respectively. The efficiency rankings were highly positively correlated under a Spearman rank correlation test. Similar to the results of Sharma et al. (1999), the variability of technical efficiencies from the DEA models was greater than from the stochastic frontier model.

Hjalmarsson et al. (1996) provided results obtained from the stochastic frontier model and DEA models. Similarity and dissimilarity depended upon the inclusion of the control variables in the stochastic frontier and sequential or intertemporal specification in the DEA frontier.

Applications of DEA to Efficiency Measurement

There is a substantial amount of literature addressing the analysis of economic efficiency in agriculture using the DEA approach. Chavas and Aliber (1993) conducted a nonparametric analysis of technical, allocative, scale, and scope efficiency of agricultural production based on a sample of 545 Wisconsin farms divided into nine agricultural districts. The outputs used in the analysis included two aggregated categories: crops and livestock. The inputs included seven categories: family labor, hired labor, miscellaneous inputs (repairs, rent, custom hiring, supplies, gas, oil, insurance, and utilities), animal inputs (purchased feed, breeding, and veterinary services), crop inputs (seeds, fertilizers, and chemicals), intermediate-run assets, and long-run assets. With an assumption that all sampled farmers in a given district faced the same prices in the year analyzed (1987), input and output quantity indexes were measured by their monetary value.

Results of the study showed that the majority of farms exhibited at least one form of inefficiency. It was found that economic losses were commonly due to allocative and scale inefficiencies, while technical inefficiencies were of limited magnitude. The analysis showed strong economies of scale for very small farms and some diseconomies of scale for large livestock operations, but not for large crop operations. It also presented evidence of important economies of scope in Wisconsin agriculture which, however, tended to decline sharply with the size of the enterprises. Furthermore, econometric analysis of the efficiency indexes suggested that the financial structure of farms can have some significant influence on their ability to attain economic efficiency.

Featherstone, Langemeier, and Ismet (1997) implemented a nonparametric analysis of efficiency for a sample of 195 Kansas beef cow farms. Output was defined as accrual gross income (minus purchased cattle), measured on a value-added basis. Six inputs were identified: feed, labor (paid and unpaid), capital (interest, repairs, depreciation, and machinery hired), utilities and fuel, veterinary expenses, and miscellaneous costs. Just as in Chavas and Aliber (1993), input and output quantity indexes were measured by their monetary value, assuming "the law of one price" for all of the analyzed farms.

Analysis indicated that, on average, the farms were 78% technically efficient, 81% allocatively efficient, and 95% scale efficient, while 68% of the farms exhibited decreasing returns-to-scale. The average overall economic efficiency for the beef cow herds was 0.60 with a standard deviation of 0.14, which indicates that, on average, the sample of farms was inefficient.

Tobit models were used in order to identify the sources of inefficiencies. Results indicated that size positively affected technical efficiency, older farmers were technically more inefficient than younger ones, and, finally, technical efficiency decreased with specialization, which could mean that economies of scope may be present in beef production in Kansas. While allocative inefficiency was not associated with any of the independent variables, farm size and specialization positively influenced scale efficiency. Also, farm size had a positive effect on overall efficiency. The leverage variable was not statistically significant with any of the Tobit models, which contradicted the results of Chavas and Aliber, who found a significant relationship between leverage and efficiency. The tenure variable was also not significant in any of the Tobit models. Examining correlation coefficients, the authors concluded that producers who had low profitability levels needed to concentrate more on reducing input use per unit of output rather than adjusting the size of their cow herd.

Thompson et al. (1990) applied multiplier bounds, which are called an Assurance Region (AR), for efficiency analysis of the linear production possibility set under DEA. The outputs used in the analysis included physical quantities of agricultural products produced. The inputs included total acres farmed, total labor hours employed in farming, total value of purchased inputs, and a depreciation value. There were 83 farms analyzed in the research. AR principles, which were introduced to technically efficient farms, reduced the number of candidates for overall efficiency from 23 to 8 under one model and from 44 to 13 under another one.

Sources of Inefficiency

Generally, there are two approaches for determining factors that affect a firm's economic efficiency. The most popular approach, defended by Kalirajan (1991) and Ray (1988), is to estimate efficiency scores and then to regress obtained scores against a set of factors that affect efficiency or to use nonparametric analysis or analysis of variance (ANOVA) tests. Another approach, defended by Kumbhakar et al. (1991) and Battese and Coelli (1995), is to directly incorporate factors that affect efficiency into the estimation of an efficiency frontier since such factors may have a direct impact on efficiency. However, as noted by Sharma et al. (1999), the DEA approach cannot easily incorporate those factors directly into the estimation of the efficiency frontier without prior assumptions about their positive or negative impacts on economic efficiency. For example, see Ferrier and Lovell, 1990. Thus, it seems appropriate to use the first procedure in this research.

Fare et al. (1990) developed a nonparametric approach to measure expenditure (credit) constraints on farm economic efficiency. Since farmers must obtain operating loans each year due to seasonality in production and significant time lags between incurred costs and received revenues, the role of credit constraints on farm profit might be important. In order to test this hypothesis, the authors constructed profit frontiers with and without expenditure constraints and then evaluated foregone profit as dual evidence for the existence of expenditure constraints.

Fare et al.'s (1990) data set did not include information on physical quantities of inputs and outputs (except for land); it only contained information in value terms. In order to measure input and output quantity indexes in monetary values, it was assumed that all of the farms in the data set faced the same input and output prices. One output, three fixed inputs, and six variable inputs were selected for the analysis. Output was defined as crop revenues since rice farms were examined. Fixed inputs included acres of land; capital equipment in dollar value; and overhead expenses, which included accounting fees, insurance, taxes, and interest. Variable inputs included materials, which included cost of fertilizer, pesticides, and custom operations; energy, which included expenditures on fuel, oil, and electricity; leased farm equipment expenditures; marketing services; labor; and purchased water.

Overall efficiency was decomposed into actual efficiency and financial efficiency. The overall efficiency measure was obtained by comparing actual profit and unconstrained, maximal potential short-run profit. Financial efficiency refers to a farm's profit loss due to the expenditure constraint, e.g., if the expenditure constraint is not binding, then financial efficiency equals one. Actual efficiency measures efficiency of the farm given existing expenditure constraints. Then, profit loss resulted from the financial inefficiency and profit loss caused by failure to achieve maximal potential profit given actual expenditure levels, or actual inefficiency, were examined. Results indicated that 13 of the 82 farms were actual efficient, while 65 farms were financially efficient. All actual efficient farms except one exhibited financial efficiency. This result suggests that actual efficient farms are also financially efficient, although financially efficient farms are not necessarily actual efficient.

Similar results were obtained by Whittaker and Morehart (1991). They demonstrated that farm expenditure constraints have caused many agricultural producers to be cost inefficient, leading to economic inefficiency.

One of the major factors affecting farm economic results is management ability or management capacity of the farmer (e.g., Kay and Edwards, 1999; Boehlje and Eidman, 1984). Rougoor et al. (1998) defines management capacity as "having the appropriate personal characteristics and skills to deal with the right problems and opportunities in the right moment and in the right way" (p. 264). They divide management capacity into two groups: 1) personal aspects, which consist of the farmer's motivation (e.g., farmer's goals and risk attitude), abilities and capabilities, and biographical facts (e.g., farmer's age, education level, and farming experience); and 2) aspects of the decision-making process which reflect the farmer's attitude towards and performance in the decision-making phases of planning, implementation, and control.

In a review of studies on farmer management capacity, Rougoor et al. (1998) concluded that researchers using frontier approaches in their studies usually look at a farmer's biographical facts as explanatory variables for farm economic efficiency, while other personal aspects of the farmer and his/her level of performance in different stages of the decision-making process are mostly ignored. Rougoor et al. (1998) also found that the influence of biographical aspects on farm economic results was not clear: sometimes an effect was found, sometimes it was not. However, in cases when the effect was found, it had different impacts on efficiency in different studies.

Productivity Growth

Lovell (1993) identifies productivity of a production unit as the ratio of its output to its input. He states that productivity of an individual firm depends on differences in production technology and differences in the efficiency of the production process, as well as on differences in the environment when and where production occurs. Due to these three factors, productivity changes over time. At a given moment of time, when technology and the production environment are essentially the same, production units may exhibit different productivity due to differences in their production efficiency. Thus, as noted by Bitran and Chang (1984), in order to achieve valid productivity measures, a DMU must be compared to itself at different time points as well as compared with other DMUs at the same point in time.

Grosskopf (1993) characterizes productivity growth as "the net change in output due to change in efficiency and technical change, where the former is understood to be the change in how far an observation is from the frontier of technology and the latter is understood to be shifts in the production frontier" (p. 165). A similar definition of productivity growth was given by Nishimizu and Page (1982): "we define technological progress as the change in the best practice frontier. …all other productivity change – for example, learning by doing, diffusion of new technological knowledge, improved managerial practice as well as short run adjustment to shocks external to the enterprise – as technical efficiency change" (p. 922).

Productivity Growth Measurement Approaches

Grosskopf (1993), in an overview of productivity measurement approaches, divided them into two different categories: non-frontier and frontier. In turn, each category was subdivided into parametric and nonparametric models.

The non-frontier nonparametric group includes index number approaches (e.g., Tornqvist index, Fischer index, and Hulten index) and growth-accounting approaches, pioneered by Solow (1957). Econometric, non-frontier approaches to productivity measurements are based on parametrizing different functional representations of technology (e.g., production function, revenue function, and cost function). Estimated parameters are used to solve for technical change and overall productivity growth. Both econometric and nonparametric non-frontier approaches are based on assumptions of technical and allocative efficiencies, thus completely ignoring inefficiency. If those assumptions are violated, then the estimated productivity indexes will be biased (Grosskopf, 1993).

Frontier approaches to productivity measurement allow for inefficiency. Parametric frontier approaches employ econometric estimation of technology. Frontiers are estimated using different techniques and by imposing restrictions on the estimated functions. In the case of estimating frontier production functions, the techniques include isolating frontier technical change (e.g., Forsund and Hjalmarsson, 1979) and identifying productivity growth as a sum of technical change and efficiency change (e.g., Nishimizu and Page, 1982; Perelman and Pestieau, 1988; Fecher and Perelman, 1989). While employment of production functions implies scalar output, employment of other functional representations of technology (e.g., distance functions, revenue functions, profit functions, and cost functions) allow for inclusion of multiple outputs (Grosskopf, 1993). For example, Bauer (1990 a) calculated total factor productivity by using a stochastic cost frontier with multiple outputs.

A popular nonparametric frontier approach to measuring productivity growth is the Malmquist productivity index calculated using linear programming techniques. The theoretical derivation of the Malmquist index and its properties was introduced by Caves et al. (1982a). Following Farrell (1957), the index was based on defining an efficiency frontier that can be identified in terms of minimizing input requirements per unit of output. The output-based and input-based productivity indexes were named for Stan Malmquist, who proposed constructing input quantity indexes as ratios of distance functions (see Malmquist, 1953). Distance functions are functional representations of multiple-output, multiple-input technology that require data only on quantities of those inputs and outputs. Thus, distance functions allow modeling the production frontier as well as deviations from it, which represent technical inefficiency and shifts in the frontier from technological change (Grosskopf, 1993).

Caves et al. (1982a and 1982b) defined Malmquist productivity of DMU k relative to DMU l as the minimum proportional decrease in all the elements of k's output vector such that the resulting output vector is producible with the input levels of DMU k and the productivity level of DMU l. In the case where DMU k has a higher level of productivity, the productivity index will be greater than one. The same concept can be used to measure productivity change over time for the same DMU.

In order to be computed, Caves et al.'s (1982a and 1982b) approach required observations of prices and certain conditions to hold. The conditions included requirements that technology was translog, second order terms were constant over time, and firms were either revenue maximizers (for the output-based index) or cost minimizers (for the input-based index). It was shown that, if those conditions held, this theoretical Malmquist index was equivalent to the Tornquist index.

The first empirical measurement of the Caves et al. (1982a) theoretical Malmquist productivity index was implemented by Fare, Grosskopf, Lindgren, and Roos in analyzing productivity growth in Swedish hospitals (1989) and Swedish pharmacies (1992). Malmquist productivity indexes were calculated using nonparametric programming techniques. The index was calculated as a geometric mean of two Malmquist productivity indexes. Use of the geometric mean avoided the choice of a particular time period as a point of reference for calculating productivity changes. Moreover, Fare et al. (1989) developed techniques which allowed decomposing productivity growth into two mutually exclusive and exhaustive components: changes in technical efficiency over time and shifts in technology over time. Later, Fare et al. (1994a) developed a technique which allowed further decomposition of the Malmquist productivity index efficiency component into a technical efficiency change component and a scale efficiency change component.

As noted by Grosskopf (1993) and Fare et al. (1994a and 1994b), Malmquist productivity indexes can be calculated in different ways: as the quotient of Tornqvist indexes (see Caves et al., 1982a) if the distance functions[1] are in translog form with identical second order terms and with additional assumptions about the absence of

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[1] The output distance function is defined as maximum proportional expansion of outputs given the input level, and the input distance function is defined as maximum proportional inputs reduction given the output level under specified technology (Fare et al., 1994b).

technical and allocative inefficiency; as a quotient of a Fisher ideal index (e.g., Balk, 1993); using a nonparametric linear-programming approach based on work of Aigner and Chu (1968); or using frontier econometric approaches (see Fecher and Perelman, 1989).

However, a review of the literature shows that estimation of the Malmquist productivity index using the nonparametric frontier approach outlined by Fare et al. (1985) has some distinct advantages over econometric and other nonparametric approaches. First, it does not require assumptions about the functional form of technology, thus minimizing specification error. A second advantage is that it does not require data on cost and revenue shares in order to determine appropriate weights for aggregation of individual inputs and outputs.

Furthermore, incorporating a large number of inputs and outputs can raise problems with the number of parameters in stochastic parametric models. In the case of the nonparametric Malmquist productivity index approach, that problem is avoided as long as there is no dimensionality problem. Also, as already noted, the Malmquist productivity index allows decomposition of estimated productivity growth into technological change and efficiency improvement with further decomposition of the latter component into technical efficiency and scale efficiency components.

The disadvantage of the nonparametric Malmquist productivity index approach as well as other nonparametric frontier approaches is that, by being non-stochastic, they group together noise and inefficiency, thus allowing for measurement error. The nonparametric approach also prevents statistical inference or hypothesis testing (Grosskopf, 1993).

Bureau et al. (1995) used three nonparametric measures of productivity (the Fisher, the Hulten, and the Malmquist indexes) to measure differences in multifactor productivity for the agricultural sectors of nine European Union countries and the United States over the period from 1973 to 1989. The Malmquist index was constructed with one aggregated output and six inputs (aggregated intermediate inputs, land, labor, machinery, buildings, and animal capital). Physical quantities were used for two inputs: hectares for land and number of hours worked for labor. All three measures yielded similar patterns of productivity growth. However, being non-frontier indexes, the Fisher and the Hulten indexes require assumptions about optimizing behavior of the analyzed units. The Malmquist index is passive regarding a firm's orientation in estimating the distance functions that create the index (Fare et al., 1994b).

Various studies (e.g., Featherstone et al., 1995; Chavas and Aliber, 1993; Featherstone et al., 1997) indicate violation of technical and allocative efficiencies in farm production. In particular, Featherstone et al. (1995) investigated the optimizing behavior of a sample of 289 Kansas farms under profit-maximization and cost-minimization hypotheses. The study used both deterministic and stochastic nonparametric tests. The deterministic results did not support strict adherence to either optimization hypothesis. The stochastic tests suggested that all 289 farms failed the profit-maximization hypothesis, whereas 171 farms failed the cost-minimization hypothesis. Allowing for non-regressive technical change did not change the basic results; 276 farms violated the profit-maximization hypothesis, and 138 farms violated the cost-minimization hypothesis. These results show the problem of incorporating behavioral assumptions into a cost or profit function estimation.

Productivity Indexes Applications

After empirical applications by Fare et al. (1989, 1992), the Malmquist productivity index has been used extensively to analyze changes in multifactor productivity. Analyzing productivity growth in 17 OECD countries over the period from 1979 to 1988, Fare et al. (1994b) calculated the Malmquist productivity indexes and their components for each country for every pair of years using gross domestic product (GDP) as the aggregate output in the model and capital stock and employment as aggregated inputs.

Ball et al. (1997) measured productivity growth in US agriculture over the period from 1948 to 1994 using procedures which are currently employed by the USDA. The USDA measures productivity growth using the Fisher index. Output was defined as gross production leaving the farm. It included the quantities of commodities sold off the farm plus net additions to inventory and quantities consumed as part of final demand in farm households. Inputs were labor, capital, and intermediate inputs. Aggregated intermediate inputs included feed, seed, livestock purchases, chemicals, and energy (fuel, natural gas, and electricity). The labor input was calculated as a product of estimates of hours worked and average compensation per hour. Capital inputs included equipment and structures, land, and beginning inventories of livestock and crops.

Although the Fisher index requires price data on inputs and outputs, the Malmquist index can be calculated using only information on physical quantities of inputs and outputs or their money value with an implicit assumption of the law of one price. Thus, inputs and outputs, which are used in productivity growth calculations by the USDA, could be used for measuring productivity growth of farms in North Dakota without information on prices faced by individual farms.

Zofio and Lovell (2001) introduced a hyperbolic Malmquist productivity index and then applied it to a US agricultural panel data set which included 48 states for the period from 1960 to 1990. It was the same data Ball et al. (1997) used in their study. The hyperbolic Malmquist productivity index, contrary to oriented indexes, considers both output augmentation and input reduction in measuring productivity growth.

Results indicated that productivity growth was increasing at an average annual rate of 1.95% per year. These results were similar to Ball et al. (1997), who generated a productivity growth rate of 2.19% per year using the Fisher index. After decomposition of the Malmquist index, technical progress was found to be a major factor for productivity growth. Efficiency improvement's contribution to productivity growth played a minor, although positive, role. However, efficiency improvement substantially contributed to the differences in productivity growth among the states.

Of particular interest are the results for North Dakota. Being among the ten best-performing states, North Dakota realized annual productivity growth of 2.11 percent from 1960 to 1990. As with most of the other states, technical change accounted for most of North Dakota's productivity growth, accounting for annual increases of 1.99 percent from 1960 to 1990. Improvements in technical efficiency averaged only 1.06 percent per year.

Tauer and Lordkipanidze (2000) employed the Malmquist index to measure the productivity of US farmers by age using 1992 census data. Results indicated that productivity increases slightly with age and then decreases. Their results also coincided with results of Zofio and Lovell (2001) in that, in most states, productivity variations are from technology use rather than efficiency differences.

Lambert and Parker (1998) examined multifactor productivity changes in Chinese agriculture. Using a data set for 27 provinces and autonomous regions from 1979-1995, they calculated a Malmquist index composed of technological and efficiency changes for a multiple-output, multiple-input production frontier. Then, using panel-data methods, the effects of various factors on productivity changes were estimated.

Arnade (1994) calculated technical efficiency and multifactor productivity measures over 1961-1987 for the agricultural sectors of 77 countries using Malmquist productivity indexes calculated using DEA. The output was defined as the total value of agricultural production. The inputs were land (in hectares), labor (the economically active population in agriculture), livestock (in head), fertilizer (in metric tons of nutrient units), and machinery (total number of wheeled and crawler tractors). Arnade also accommodated differential rates of adoption of new technologies in his definition of technical inefficiency. Slow adopters might be technically inefficient in comparison to the rapid adopters.

Suhariyanto (2000) addressed the dimensionality problem while calculating Malmquist productivity indexes for 18 Asian countries over the period from 1961 to 1996. In order to avoid the dimensionality problem, Suhariyanto constructed a Malmquist productivity index with sequential frontiers instead of contemporaneous frontiers, which are usually used in empirical studies. Sequential frontiers exclude the possibility of technological decline. The output and inputs used in the study were the same as those used by Arnade (1994).

Kao (2000) measured the performance improvement of DMUs over time using two different nonparametric approaches. Under the first approach, he treated the same DMU at two time points as two different DMUs. Then, a conventional DEA model was applied to all of the DMUs in order to calculate their efficiency scores. The ratio of the efficiency scores of two time periods for a DMU showed the efficiency improvement of that DMU.

Under the second approach, the Malmquist productivity index was utilized. The results were consistent in both methods. However, it was found that the Malmquist productivity index was more informative, which is an expected result since under the first approach, the production frontier is constructed using combined data from both periods, which prevents technological regress. Thus, if technological change is negative, it will be shown as a decline in efficiency. Misleading results may also be obtained due to the fact that under the efficiency ratio method, only one production frontier is constructed. Thus, some DMUs may have an efficiency ratio of one (lie on the production frontier) in both periods as estimated by the efficiency ratio method while performing relatively better or worse than before.

Other studies that used Malmquist multifactor productivity indexes include Mao and Koo (1997), who used the DEA approach to analyze total factor productivity in Chinese agricultural production from 1984 to 1993; Thirtle et al. (1995), who examined sources of agricultural productivity growth in 22 countries in sub-Saharan Africa; and Nyariki and Thirtle (2000), who measured productivity growth at the smallholder farm-level in Kenya.

Conclusion

Productivity growth may be achieved through technical change and/or efficiency improvement. Technical change refers to the change in technology which results in an upward shift of the production frontier. Efficiency improvement refers to more efficient use of various resources under current technology, which allows a DMU to move closer to the existing frontier.

Economic efficiency of the firm is the product of technical and allocative efficiency. If economies of scope and scale are present in the industry, then economic efficiency also includes scope and scale efficiency.

The measurement of productivity growth and economic efficiency can be implemented with various approaches: non-frontier and frontier, econometric and nonparametric. Frontier approaches strictly dominate non-frontier ones due to their ability to differentiate technical change from DMU inefficiency. Neither econometric nor nonparametric approaches seem to dominate each other. Currently, econometric methods are used more frequently in measurement of productivity growth and economic efficiency in agriculture. Certain advantages of nonparametric models make them preferable for use in this study. Specifically, the advantages of using DEA and the Malmquist productivity index approaches include

1) they do not require assumptions about the functional form of technology, thus minimizing specification error;
2) they do not require data on cost and revenue shares in order to determine appropriate weights for aggregation of individual inputs and outputs;
3) incorporating a large number of inputs and outputs can raise problems with the number of parameters in stochastic parametric models, while in the case of the nonparametric DEA and the Malmquist productivity index approaches, that problem is avoided, as long as there is no dimensionality problem; and

4) the Malmquist productivity index allows decomposition of estimated productivity growth into technological change and efficiency improvement with further decomposition of the latter component into technical efficiency and scale efficiency components.

CHAPTER III. MODEL DEVELOPMENT AND DATA

Introduction

The objective of this research is to examine the production efficiency and productivity growth of North Dakota farms and to identify whether there is a relationship between a farm's production efficiency and its financial performance. The first part of the chapter consists of the description of DEA output-oriented models, which provide an assessment of relative technical and scale efficiencies of the farms. The second part is focused on the discussion of the Malmquist TFP index that is used to calculate productivity growth. The third part consists of a description of econometric models. A Tobit model is employed to assess the influence of selected farm-specific factors on estimated technical efficiency scores. Next, two OLS models are used to determine what influence technical and scale efficiencies and the Malmquist TFP indexes have on the farms' return-on-assets (ROA). A full description of data used in the research is given in the final part of the chapter.

Methodology

Technical and Scale Efficiency

Technical and scale efficiencies are estimated by employing Data Envelopment Analysis (DEA), the nonparametric mathematical programming approach for a frontier analysis of inputs and outputs introduced by Charnes et al. (1978). One of the main advantages of the nonparametric approach is that the construction of the production frontier does not require any assumptions about the functional relationship between inputs and outputs. The DEA model uses input and output data from each farm to construct a nonparametric production frontier such that all observed farms lie on or below the envelopment frontier. Therefore, the productive efficiency of each farm is measured relative to the productive efficiencies of all other farms in the sample.

DEA models can be either output or input oriented. In the output-oriented models used for this research, the objective is to produce the maximum possible output given the input levels.

The envelopment surface of the oriented models can be either constant returns-to-scale (CRS) or variable returns-to-scale (VRS). Under CRS, the form of the envelopment surface of the constructed production frontier is a conical hull, while under VRS, it is a convex hull.

An output-oriented CRS model, developed by Charnes, Cooper, and Rhodes (1978) and referred to in the literature as the CCR model, is defined as

$$\begin{aligned} &\underset{\theta,\lambda,s^+,s^-}{Maximize} \quad z_k = \theta_k + \varepsilon \cdot \vec{1}s^+ + \varepsilon \cdot \vec{1}s^- \\ &Subject\ to: \quad \theta_k Y_k - Y\lambda + s^+ = 0 \\ &\qquad X\lambda + s^- = X_k \\ &\qquad \lambda,\ s^+,\ s^- \geq 0 \end{aligned} \tag{3.1}$$

where Y denotes an s×n matrix of output measures; X denotes an m×n matrix of input measures; $X_k = \{x_{ik}\}$ denotes amounts of inputs (i = 1, 2, …, m) employed by farm k (k = 1, 2,…, n); $Y_k = \{y_{rk}\}$ denotes amounts of outputs (r = 1, 2, …, s) produced by farm k; s^+ and s^- are slack variables; λ is an intensity (weight) vector; ε is a non-Archimedean (infinitesimal) constant; $\vec{1}$ are row unit vectors of dimension $1 \times s$ (outputs) and $1 \times m$ inputs; and θ is a scalar defining the proportional augmentation applied to all outputs of farm k.

Non-zero elements of the optimal λ identify the set of dominating producers on the production frontier, against which the producer *k* is evaluated. Dominating producers are on the frontier and define the reference point for the DMU *k*. Presence of the non-Archimedean (infinitesimal) constant in the objective function allows the maximization over θ to preempt the minimization involving slack variables, e.g., regardless of the values of s^+ and s^-, their multiplication by ε will not allow them to have any impact on θ.

The optimization is computed in a two-stage process. First, maximum augmentation of outputs is achieved by obtaining the optimal value of θ^*. In a second stage, the DMU is moved onto the efficient frontier via slack variables s^{+*} and s^{-*} (Charnes et al., 1997).

The linear programming problem (3.1) is solved *n* times, once for each farm *k*. The optimal solution to each problem, θ^*, which satisfies $1 \leq \theta^* \leq \infty$, measures the maximal proportional increase in output levels for the *k*-th farm with inputs held constant. Hence, $1/\theta^*$ measures technical efficiency of the *k*-th farm, where the technical efficiency score will lie between zero (inefficient) and one (efficient). If θ = 1, no increase in outputs is possible, which means the farm lies on the frontier and is thus technically efficient under Farrell's definition.

The output-oriented VRS model is obtained from the CRS model by adding a convexity constraint $\vec{1}\lambda = 1$ to the CCR model (3.1). The model was developed by Banker, Charnes, and Cooper (1984) and is called the output-oriented BCC model. It is defined as

$$\begin{aligned}
&\underset{\theta,\lambda,s^+,s^-}{Maximize} \quad z_k = \theta + \varepsilon \cdot \vec{1}s^+ + \varepsilon \cdot \vec{1}s^- \\
&Subject\ to: \quad \theta_k Y_k - Y\lambda + s^+ = 0 \\
&\qquad X\lambda + s^- = X_k \\
&\qquad \vec{1}\lambda = 1 \\
&\qquad \lambda,\ s^+,\ s^- \geq 0
\end{aligned} \tag{3.2}$$

Solving both models for each farm results in technical efficiency measurements under the two assumptions of CRS and VRS. The absence of the convexity constraint $\bar{1}\lambda = 1$ in the CCR model makes it less restrictive in comparison to the BCC model. Particularly, it enlarges the feasible region for the farms from the convex hull in the BCC model to the conical hull in the CCR model. An enlargement of the feasible region for the BCC model means that under the assumption of CRS, the number of efficient farms is expected to be less than under the assumption of VRS. An enlargement of the feasible region for the BCC model also implies that if a farm is efficient under the CCR (CRS) model, it will also be efficient under the BCC (VRS) model, but the reverse relationship does not necessarily hold.

Scale efficiency is computed as the ratio of the measure of technical efficiency calculated under the assumption of CRS to the measure of technical efficiency calculated under the assumption of VRS (Banker et al., 1984; Fare et al., 1985). Hence, if the technical efficiency score of the analyzed farm under the CCR model differs from the technical efficiency score under the BCC model, it indicates that the farm is not producing in the range where CRS holds and potential efficiency gains could be realized with a change in the farm size. However, as noted by Banker and Thrall (1992), this concept of returns-to-scale is well defined only for the farms that are technically efficient under the BCC model, but do not lie on the production frontier under the CCR model. For the farms that lie below the production frontier under the BCC model, productivity changes due to returns-to-scale are confounded with productivity changes due to the elimination of inefficiency.

Productivity Growth

Productivity growth of the farms is estimated and examined by calculating the Malmquist total factor productivity (TFP) indexes. The index is constructed from the ratios of distance functions, which provide a very general description of the technology, especially when technology involves many inputs and outputs (Cornes, 1992). Advantages of the Malmquist TFP indexes over traditional TFP indexes include

1) only data on quantities of inputs and outputs are required to calculate the index;
2) the index requires less restrictive assumptions about technology than other indexes;
3) it allows for inefficiency;
4) no assumptions about producer-optimizing behavior are necessary; and
5) it does not require an econometric estimation (Grosskopf, 1993; Bureau et al., 1995).

Let S^t be the production technology available at time period $t = 1,\ldots,$T such that

$$S^t = \{(x, y) : x \text{ } can \text{ } produce \text{ } y \text{ } at \text{ } time \text{ } t\}, \tag{3.3}$$

where $x \in \Re_+^n$ is a vector of inputs used to produce vector of outputs $y \in \Re_+^m$. Assuming that set S^t satisfies standard properties[1] as outlined in Shephard (1970) and following him, the output distance function D_o at time t is defined as

$$\begin{aligned} D_o^t(x^t, y^t) &= \inf\{\theta : (x^t, y^t / \theta) \in S^t\} \\ &= (\sup\{\theta : (x^t, \theta \, y^t) \in S^t\})^{-1}. \end{aligned} \tag{3.4}$$

[1] 1). Inaction is possible, i.e., given any input vector, it is always possible to produce no output.
2). There is a weak disposability of outputs.
3). Finite amounts of inputs can produce finite amounts of outputs.
4). For all inputs, output sets are closed sets.

The output distance function is defined as the inverse of the maximum proportional expansion of output vector *y* given input vector *x* under specified technology S^t. It is the reciprocal of the output-based Farrell measure of technical efficiency and homogeneous of degree +1 in outputs. This function completely characterizes technology at time *t* (Fare et al., 1994b). Particularly, $D_o^t(x^t, y^t)$ is less or equal to one if and only if $(x^t, y^t) \in S^t$. $D_o^t(x^t, y^t) = 1$ indicates that netput vector (x^t, y^t) lies on the technology frontier. Following Farrell (1957), $D_o^t(x^t, y^t) = 1$ means that the observed DMU is technically efficient and it produces the maximum amount of outputs given its inputs values. If $D_o^t(x^t, y^t) < 1$, then the DMU is technically inefficient and lies within the technology frontier, implying that proportional expansion of outputs is possible for this DMU given its input values.

Similarly, an output distance function D_o at time *t+1* is defined as

$$\begin{aligned} D_o^{t+1}(x^{t+1}, y^{t+1}) &= \inf\{\theta : (x^{t+1}, y^{t+1}/\theta) \in S^{t+1}\} \\ &= (\sup\{\theta : (x^{t+1}, \theta\, y^{t+1}) \in S^{t+1}\})^{-1}. \end{aligned}$$

(3.5)

Furthermore, definition of the Malmquist TFP index requires obtaining distance functions with respect to two different time periods, such as

$$D_o^t(x^{t+1}, y^{t+1}) = \inf\{\theta : (x^{t+1}, y^{t+1}/\theta) \in S^t\} \tag{3.6}$$

and

$$D_o^{t+1}(x^t, y^t) = \inf\{\theta : (x^t, y^t/\theta) \in S^{t+1}\}. \tag{3.7}$$

In the first mixed-period distance function, the input-output vector (x^{t+1}, y^{t+1}) belongs to the period *t+1*, while the technology S^t is from period *t*. Thus, the function measures maximum proportional change in outputs given the set of inputs relative to technology existing at the previous period *t*. Similarly, the second distance function (3.7) measures the maximum proportional change in outputs given the set of inputs relative to the technology at time period *t+1*.

Since observations (x^t, y^t) and (x^{t+1}, y^{t+1}) in both functions may not be the elements of the technologies S^t and S^{t+1}, respectively, the corresponding values of distance functions may exceed unity. Exceeding unity for distance functions will occur whenever the netput vector being evaluated is not feasible under the technology existing in the other period. Particularly, if the value of the distance function, which evaluates netput (x^{t+1}, y^{t+1}) under technology S^t, is greater than one, it means that there has been a shift in the production frontier *S* from *t* to *t+1*. In other words, there has been technological change between periods *t* and *t+1*.

Caves et al. (1982a) define an output-based Malmquist productivity index with reference technology in time period *t* as

$$M_o^t = \frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)} \tag{3.8}$$

and, alternatively, an output-based Malmquist productivity index with reference technology in time period *t+1* as

$$M_o^{t+1} = \frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^t, y^t)}. \tag{3.9}$$

Fare et al. (1989) defined the output-based Malmquist productivity index as the geometric mean of the two indexes specified above:

$$M_o(x^{t+1}, y^{t+1}, x^t, y^t) = \left[\left(\frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)}\right)\left(\frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^t, y^t)}\right)\right]^{1/2}, \tag{3.10}$$

which avoids making an arbitrary choice of selecting either one of the analyzed time periods as a reference point.

Following Fare et al. (1989, 1992), the Malmquist index can be decomposed into two components:

$$M_o(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{D_o^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_o^t(x^t, y^t)}\left[\left(\frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^{t+1}, y^{t+1})}\right)\left(\frac{D_o^t(x^t, y^t)}{D_o^{t+1}(x^t, y^t)}\right)\right]^{1/2}, \quad (3.11)$$

where the first component (the ratio outside the brackets) measures efficiency change, or how the position of the observed DMU has changed relative to the production frontier between periods t and $t+1$. The second component inside the brackets measures technical change, or how the production frontier shifted between periods t and $t+1$.

The Malmquist TFP index may be calculated under any technological assumptions regarding returns-to-scale. Calculating the index in (3.11) under the assumption of CRS, an efficiency change component of the index can be further decomposed into two parts: a pure efficiency change component and a scale change component. A pure efficiency change component is calculated in the same way as an efficiency change component, only under the assumption that technology exhibits VRS. The scale change component is a ratio of the efficiency change component to the pure efficiency change component.

Following Fare et al. (1994b), the Malmquist TFP index is calculated using nonparametric programming techniques. For a given panel of k farms using inputs and outputs ($x_n^{k,t}$, $y_m^{k,t}$), the frontier technology in period t can be constructed as

$$\begin{aligned} S^t = \{(x^t, y^t) : y_m^t &\le \sum_{k=1}^{K} \lambda^{k,t}\, y_m^{k,t} \quad , \quad m = 1,\ldots, M \\ x_n^t &\ge \sum_{k=1}^{K} \lambda^{k,t}\, x_n^{k,t} \quad , \quad n = 1,\ldots, N \qquad (3.12) \\ \lambda^{k,t} &\ge 0 \quad , \quad k = 1,\ldots, K \quad \} \quad , \end{aligned}$$

where $\lambda^{k,t}$ denotes the intensity variable, which indicates at what intensity each activity can be employed in production. As shown in Fare et al. (1985), the reference technology S^t in (3.12) exhibits strong disposability in inputs and outputs as well as constant returns-to-scale. Following Afriat (1972), it can be shown that constant returns-to-scale may be relaxed to allow for variable returns-to-scale by adding the following restriction: $\sum_{k=1}^{K} \lambda^{k,t} = 1$. The frontier technology S^t is defined as the efficiency frontier derived from DEA models (3.2) assuming CRS and (3.1) assuming VRS.

In order to calculate the productivity change of farm *k* between time periods *t* and *t + 1*, six different linear programming problems have to be solved. These problems are distance functions for both time periods $D_o^t(x^t, y^t)$ and $D_o^{t+1}(x^{t+1}, y^{t+1})$ relative to the CRS technology, distance functions for both time periods $D_o^t(x^t, y^t)$ and $D_o^{t+1}(x^{t+1}, y^{t+1})$ relative to the VRS technology, and distance functions for mixed periods $D_o^{t+1}(x^t, y^t)$ and $D_o^t(x^{t+1}, y^{t+1})$ (Fare et al., 1994a).

Given the fact that the output distance function is the reciprocal of the Farrell output-based measure of technical efficiency, the output distance function is computed for each farm $k^{'}$ at time *t* under the assumption of CRS, given the production possibility set S^t, as a solution to the following linear programming problem:

$$
\begin{aligned}
&(D_0^t(x^{k',t}, y^{k',t}))^{-1} = Maximize\ \theta^{k^{'}} \\
&Subject\ to: \quad \theta^{k^{'}} y_m^{k^{'},t} \le \sum_{k=1}^{K} \lambda^{k,t} y_m^{k,t} \\
&\qquad\qquad\quad \sum_{k=1}^{K} \lambda^{k,t} x_n^{k,t} \le x_n^{k',t} \\
&\qquad\qquad\quad \lambda^{k,t} \ge 0,
\end{aligned} \tag{3.13}
$$

which is identical to (3.2) and follows that $\theta^{k'}$ is the DEA measurement of the $D_o^t(x^t, y^t)$.

Computation of $D_o^{t+1}(x^{t+1}, y^{t+1})$ under the assumption of CRS is exactly the same as (3.13), with the only difference that *t+1* is substituted for *t*:

$$\begin{aligned}
&(D_0^{t+1}(x^{k',t+1}, y^{k',t+1}))^{-1} = Maximize\ \theta^{k'} \\
&Subject\ to: \quad \theta^{k'} y_m^{k',t+1} \le \sum_{k=1}^{K} \lambda^{k+1,t+1} y_m^{k+1,t+1} \\
&\qquad \sum_{k=1}^{K} \lambda^{k+1,t+1} x_n^{k+1,t+1} \le x_n^{k',t+1} \\
&\qquad \lambda^{k,t+1} \ge 0.
\end{aligned} \tag{3.14}$$

Farm *k* will be technically efficient in a given time period if and only if its output distance function equals one in that time period. Technically efficient farms will define the production frontier in each of the time periods *t*, while technically inefficient farms will lie below the production frontier. Placing the additional restriction $\sum_{k=1}^{K} \lambda^{k,t} = 1$ on the intensity variable λ in problems (3.13) and (3.14) allows computing distance functions $D_o^t(x^t, y^t)$ and $D_o^{t+1}(x^{t+1}, y^{t+1})$ relative to the VRS technology.

The mixed-period distance functions, which are used to calculate technical change, are computed as follows. The output distance function for farm *k* at time period *t+1* under the assumption of CRS, given the production possibility set S^t, is computed as the solution to the following linear programming problem:

$$\begin{aligned}
&(D_0^t(x^{k',t+1}, y^{k',t+1}))^{-1} = Maximize\ \theta^{k'} \\
&Subject\ to: \quad \theta^{k'} y_m^{k',t+1} \le \sum_{k=1}^{K} \lambda^{k,t} y_m^{k,t} \\
&\qquad \sum_{k=1}^{K} \lambda^{k,t} x_n^{k,t} \le x_n^{k',t+1} \\
&\qquad \lambda^{k,t+1} \ge 0.
\end{aligned} \tag{3.15}$$

As noted earlier, since (x^{t+1}, y^{t+1}) may not be included in S^t, the output distance function $D_o^t(x^{t+1}, y^{t+1})$ may achieve values greater than one. $D_o^t(x^{t+1}, y^{t+1})$ will exceed unity when (x^{t+1}, y^{t+1}) is not feasible given the production possibility set S^t. Finally, the output distance function $D_o^{t+1}(x^t, y^t)$ is found by solving problem (3.15) with interchanged superscripts t and $t+1$.

Technical and scale efficiencies and Malmquist TFP indexes are estimated for each farm in the data set using the General Algebraic Modeling Systems (GAMS) program for Windows NT/95/98, Version 2.50A. The code for the model is presented in Appendix A.

Sources of Technical Efficiency

Measures of technical efficiency obtained from (3.13) are used in regression analysis to estimate the relationship between the efficiency measures and different farm characteristics. The following model is estimated:

$$\begin{aligned} TE = f(&REGION, YEAR, FTYPE, DARC, DARI, DARL, NFTFIR, \\ &YRSFARM, INSUR, GOVT, ACRGRINC), \end{aligned} \tag{3.16}$$

where TE represents the technical efficiency scores. Variables hypothesized to influence technical efficiency include farm location (REGION); year analyzed (YEAR); farm type (FTYPE); short term debt-to-asset ratio (DARC); intermediate term debt-to-asset ratio (DARI); long term debt-to-asset ratio (DARL); non-farm income to total farm income ratio (NFTFIR); experience, which is measured as a number of years in the farm business (YRSFARM); amount of insurance (INSUR) and governmental (GOVT) payments made to the farm; and accrual gross income (ACRGRINC).

Variables REGION and YEAR are included in the model to test for the group (REGION) and time (YEAR) effects. Group effects may be present because of the heterogeneity of inputs and outputs between farms in different regions, while distribution of efficiency measures from year to year may vary due to weather conditions or other factors that influence the agricultural production level, such as pest outbreak or crop or livestock diseases. In the model, Region 1 corresponds to the Red River Valley, Region 2 to the North Central, Region 3 to the South Central, and Region 4 to the Western Missouri Slope (Swenson, 2001).

Variable FTYPE measures the impact of farm specialization on technical efficiency. Following Swenson (2001), farms were classified as "crop" (FTYPE 1) if 70% or more of their accrual income was from crop enterprises, as "livestock" (FTYPE 2) if 70% or more of the accrual income was from livestock enterprises, and "mixed" (FTYPE 3) if they did not belong to either one of the previous groups. Assuming a strong positive relationship between farm financial performance and efficiency, and given Swenson's (2001) results, it is hypothesized that crop farms have higher efficiency scores than mixed farms, and the latter have higher efficiency scores than livestock farms.

The debt-to-asset ratios (DARC, DARI, and DARL) measure the impact of financial leverage on technical efficiency. Debts and assets are classified according to expected duration: one year for current debts and assets, from one to ten years for intermediate, and more than ten years for the long term. It is difficult to hypothesize the relationship between financial leverage and technical efficiency.

According to the Fisher separation theorem, under the hypothesis of perfect financial markets, investment and financing decisions are independent (Robinson and

Barry, 1996; Silberberg, 1990). Hence, the optimal capital structure of a firm is solely determined by the leverage ratio where the average cost of debt equals the rate of return on productive investments. Thus, a firm should have the same efficiency level regardless of the way it is capitalized and, consequently, there should not be any significant statistical impact of leverage on technical efficiency. Alternatively, the agency cost, free cash flow, and credit evaluation concepts of finance theory provide possible explanations for the potential relationship between financial leverage and farm-level efficiency (Nasr et al., 1998).

The agency cost concept implies that monitoring, bonding, and adverse incentive costs (e.g., excessive risk taking and/or unintended use of borrowed funds by the borrower) are largely passed on by lenders to borrowers through interest rates adjustments, origination fees, collateral requirements, etc. (Ellinger and Barry, 1991). These costs, in turn, may reduce the borrower's technical efficiency and hinder business performance (Nasr et al., 1998). Therefore, the agency cost concept implies a negative relationship between technical efficiency and financial leverage.

The free cash flow concept, developed by Jensen (1986), proposes that obligations may lead to stronger incentive compatibility between principals and agents. In the agricultural setting, this concept suggests that farmers with higher debt obligations will be induced to exert greater efforts on behalf of lenders (Barry and Robinson, 2001). Therefore, the free cash flow concept implies a positive relationship between short-term financial leverage and technical efficiency.

The credit evaluation concept suggests that lenders will prefer to finance more efficient producers since those farmers have lower credit risks. Agricultural bankers often use management/efficiency variables along with financial variables in evaluating a farmer's creditworthiness (Ellinger et al., 1992). Thus, use of higher financial leverage by some producers could represent recognition of their better technical efficiency because of the lender's positive evaluation of their creditworthiness (Nasr et al., 1998). Barry et al.'s (1981) findings indicate that agricultural lenders constrain capital loans more than operating loans because variations in the farmer's recent financial performance are often explained by the factors beyond the farmer's control. Barry et al.'s (1981) results, in turn, suggest that the credit evaluation concept implies a positive relationship between intermediate and long-term financial leverages and technical efficiency.

While Featherstone et al.’s (1997) and Rowland et al.'s (1998) results support the perfect financial markets hypothesis, Chavas and Aliber (1993) and Nasr et al. (1998) provided evidence of a lack of separation between financing and production, thus supporting free cash flow and credit evaluation concepts of finance theory. Chavas and Aliber (1993) found no significant effect of the current debt-to-asset ratio, but positive and significant effects of intermediate and long term debt-to-asset ratios on technical efficiency. Nasr et al. (1998) found no significant effect of the total debt-to-asset ratio, but positive and significant effects of the current debt-to-asset ratio on technical efficiency.

The variable NFTFIR is hypothesized to have a negative effect on farm technical efficiency because part-time farmers cannot allocate all of their work time to farming and therefore may not be able to take advantage of optimal timing of farming operations (e.g., optimal weather conditions).

It is hypothesized that farmer experience, measured here in terms of years that the producer has been farming (YRSFARM), does not have any significant effect on TE.

While farmers that have been farming for a longer period of time may have learned from past experiences and thus would have improved management abilities and, consequently, better efficiency, farmers that have not farmed long may have better education or be more receptive to innovations. Rougoor et al. (1998), while reviewing results of other studies, concluded that the influence of experience and/or age of the farmers on farm efficiency was not straightforward.

Both insurance (INSUR) and government payments (GOVT) are hypothesized to be negatively correlated with TE. Since insurance and government payments were not included in the outputs in the DEA model, these payments and TE scores are expected to be substitutes. A producer may have low TE scores due to adverse weather conditions or crop or livestock diseases. However, in that case, the farmer would receive insurance payments for the lost crops or animals. Similarly, since outputs in the DEA model are measured as terms of accrual revenues, low market prices for certain crops will lower TE scores, but will induce government payments which may offset lowered TE indexes.

Finally, accrual gross income (ACRGRINC) is included in the model to test whether there is a relationship between farm size and TE. Although farm size is usually measured in acreage, it seems more appropriate to measure farm size in terms of accrual gross income, since farms are not homogeneous in producing outputs and land values differ significantly between regions. It is hypothesized that there is a positive relationship between farm size and technical efficiency due to economies of scale. Smaller farms tend to be less efficient and lie further away from the efficient frontier (Hall and Leveen, 1978).

Since the dependent variable (technical efficiency scores) is restricted to the range (0, 1], then ordinary least squares (OLS) estimates are inconsistent (Greene, 1997). One of the possible solutions to overcome these problems would be to employ for the analysis a two-limit Tobit model (see Greene, 1997). For similar purposes, the Tobit model was employed by Chavas and Aliber (1993), Featherstone et al. (1997), Rowland et al. (1998), and Bravo-Ureta and Pinheiro (1997).

The Tobit model is estimated as follows:

$$\begin{aligned} TE &= V_k\beta + \varepsilon_i, \qquad if \quad V_k\beta + \varepsilon_i < 1; \\ &= 1, \qquad\qquad\quad otherwise, \end{aligned} \tag{3.17}$$

where V_k is a vector of explanatory variables described above for farm k, β is a vector of parameters to be estimated, and ε_k is an error term distributed N(0, σ^2).

Profitability, Efficiency, and Productivity

Two models are estimated in order to analyze how profitability of individual farms is related to their technical and scale efficiency and to determine if changes in farm productivity have an impact on a farm's financial performance.

Rate of return-on-assets (ROA) was chosen as a measure of a farm's financial performance. According to the perfect capital market hypothesis and the Fisher separation theorem, the decision of leverage is independent of farm efficiency and productivity. Therefore, there should not be a difference between choosing ROA or the rate of return-on-equity (ROE) as an appropriate measure of a farm's financial performance for the purposes of this analysis. However, since interest payments were not included in the model while calculating farm efficiency and productivity, they should not be accounted for while choosing the appropriate measure of farm financial performance. Also, some producers may have to pay higher interest rates than others, and that fact could bias the results of the estimation. Thus, ROA is selected as a profitability measure for the analysis.

Return-on-assets is calculated as net farm income plus interest expense minus a charge for unpaid operator labor and management, divided by average total assets (Swenson, 2001). All assets are evaluated on a cost basis, and unpaid operator labor on each farm was assessed an equal charge per full time operator (e.g., $15,000 for 2,000) plus five percent of gross revenue (Swenson, 2001).

To find out how a farm's returns-on-assets are influenced by technical and scale efficiencies and by previous financial performance, the following econometric model is estimated:

$$ROA_{k,t} = f(TE_{k,t}, SE_{k,t}), \tag{3.18}$$

where $ROA_{k,\ t}$ is farm k's rate of return-on-assets in year t. The explanatory variables include technical efficiency ($TE_{k,\ t}$) and scale efficiency ($SE_{k,\ t}$) scores.

Another econometric model is estimated in order to evaluate the impact of productivity on ROA:

$$ROA_{k,\ t} = f\ (MALMQTFP_{k,\ t}), \tag{3.19}$$

where $MALMQTFP_{k,\ t}$ is the Malmquist TFP index of farm k between years $t\text{-}1$ and t.

It is hypothesized that all three independent variables from both models have positive influences on ROA. Increases in efficiency and productivity should result in increases in a farm's financial performance, as measured by ROA. Also, over a few years of observations, the impact of short-term random fluctuations in production on the farm's financial performance as well as on estimation of farm efficiency and productivity should be eliminated. Inclusion of several years of observations should strengthen the results compared to a cross-section model or a panel model with only two or three years of data.

All regression models are estimated using the Statistical Analysis System (SAS) program. The code for models described above is presented in Appendix B.

Data

Data for conducting the research were obtained from the North Dakota Farm and Ranch Business Management Education (NDFRBM) program data set. The NDFRBM has been collecting farm records since 1989. Currently, there are more than 700 farms enrolled (Swenson, 2001). Every year, some farms leave the program and new ones join. Also, some farms submit only general farm records, while others provide detailed data for the enterprise analysis.

In order to be able to calculate input and output variables for the DEA models, only farms that submitted enterprise level data could be included in the analysis. After further exclusion of farms that did not participate in the program for the time period of the analysis and farms with inconsistent or incomplete records, 130 farms remained for the seven-year period (1995 to 2001). Fifty-five of the farms had only crop enterprises, while the rest produced both crop and livestock outputs.

The analysis is conducted at the state and regional level. There are 26 farms from Region 1 in the analyzed sample, 43 farms from Region 2, 39 farms from Region 3, and 22 farms from Region 4. Farmers in different regions generally face different agro-climatic conditions and specialize in different mixes of crop and livestock production. For example, Red River Valley farms typically have smaller total acreage, but much larger total farm sales, assets, and liabilities than farms in all other regions. The occurrence of mixed and livestock enterprise farms ranges from less than 1% in the Red River Valley to 68% in the Western Missouri Slope region (Swenson, 2001).

To estimate efficiency and productivity, whole farm data and data from the enterprise analysis were aggregated to obtain five inputs and two outputs. Outputs include 1) crop, and 2) livestock. Inputs consist of: 1) labor, 2) operating expenses, 3) crop acres, 4) pasture acres, and 5) capital.

Problems arose while measuring output and some input quantities. There were a total of 27 livestock and 57 crop enterprises (see Appendix A) produced during the time period. Because of such heterogeneity of outputs, it was not possible to construct output quantity indexes. Thus, both outputs are measured in terms of accrual revenues from all crop and livestock enterprises, respectively.

Outputs were calculated as a market price received multiplied by actual quantity produced. All products produced by each of the farm enterprises were included in the outputs, while insurance and government payments were excluded from the output measures. Some farmers produced crops on a share-rent basis. In that case, outputs included the entire crop produced, not only the producer's share. The operating expenses were adjusted for the amount paid by the landlord as well. These adjustments were done in order to smooth out the differences in inputs used and outputs produced between share-rent farmers and full tenants and cash-rent farmers, since those differences were not attributed to efficiency and productivity differences.

In order to calculate unbiased measures of efficiency and productivity, input and output prices were adjusted by the annual average indexes of prices received for farm outputs and indexes of prices paid for farm inputs, with 1990 to 1992 prices being a benchmark level (e.g., index for 1990 to 1992 equals 1.00). Since indexes for each of the crop and livestock products were not available, all crops were aggregated into four categories, food grains, feed crops, oil-bearing crops, and other crops (dry edible beans and sugar beets), while livestock outputs were divided into two categories, meat products and dairy products. Prices for outputs were divided by the indexes corresponding to each category. The results were two output measures aggregating over all crops and all livestock.

On the input side, only operating expenses were adjusted for price changes between years, since it was not possible to separate capital expenses incurred each year. Since data on expenditures for each category of operating expenses (e.g., fuel, seed, chemicals, and feed) were not available, it was assumed that all farmers in the sample had a similar mix of operating expenses. Actual operating expenses were adjusted by the average annual index of prices paid for all inputs.

The labor input is measured in work hours and consists of three categories: total amount of paid full-time hours, paid part-time hours, and unpaid operator hours per year. The limitation with the labor data is that not all producers submitted records for the amount of unpaid operator labor hours. For those farmers who did not have those records, the amount of unpaid operator labor was imputed based on the farm enterprise mix and estimated number of hours attributed to each of those enterprises.

Because operating expenses are an aggregated input, it is measured in monetary value. Actual operating expenses were adjusted for paid labor costs, since labor is a separate input in the model; for interest and cash-rent payments because those payments do not correspond to efficiency and productivity measures; for share-rent expenses made by the landlord, as mentioned before; and for prepaid and accounts payable inventory changes. Operating expenses are thus calculated on an accrual basis.

Crop acres are calculated as total crop acres farmed regardless of land tenure. Acres under the CRP program are included in the crop acres input variable as well. Pasture acres are computed as the total number of pasture acres used by the farm.

Finally, capital, being an aggregate input, is measured in monetary value. It is calculated as a sum of machinery and equipment, buildings and improvements, breeding livestock, and other capital assets, which, in turn, were calculated as a sum of beginning and ending inventories divided by two. All capital assets are measured on a cost basis.

Table 3.1 provides summary-descriptive statistics for the inputs and outputs, for variables that were used in the estimation of the relationship between farm financial performance and efficiency and productivity scores, and for the farm-specific variables that were hypothesized to influence technical efficiency. Given large variation in the data, it is expected that there would also be a large variation in individual farm efficiency and productivity indexes.

Some farmers had negative values of NFTFIR, which implies that those producers incurred losses in the farm business while receiving positive income from other sources. One of the most noticeable trends from Table 3.1 is that all mean values of inputs (except for labor) and outputs had been steadily increasing throughout the 1995 to 2001 years. Since prices of outputs and operating expenses are adjusted to the 1990 to 1992 level, this trend could indicate an increase in average farm size and level of operations.

Several limitations with the data set should be mentioned. First, farms in the analysis do not represent all North Dakota farms. Farmers participating in the NDFRBM program, especially those who participated for seven consecutive years, tend to outperform average state producers. Second, since each farm has its own unique aspects, the most

Table 3.1. Input and Output Variables for North Dakota Farms Sampled: Summary Statistics

Year		*Crop Output, $*	*Livestock Output, $*	*Labor, hrs*	*Operating Expenses, $*	*Crop Land, ac*	*Pasture, ac*	*Capital, $*
1995	MEAN	164809	39500	2995	131859	1549	462	224698
	STDEV	132801	60436	1848	87681	864	760	138675
	MIN	18831	0	1000	17759	172	0	11144
	MAX	720921	383401	20122	510218	6380	3621	1017535
1996	MEAN	166577	43301	3067	138946	1624	466	248175
	STDEV	132353	65286	1520	83583	891	779	148062
	MIN	17236	0	1000	26910	305	0	25106
	MAX	747517	444057	12300	499080	6343	3721	1110702
1997	MEAN	173822	45500	2918	149811	1734	478	273217
	STDEV	130535	69570	1128	94381	979	783	174757
	MIN	23826	0	1000	22270	309	0	36267
	MAX	626509	472050	8800	484162	6241	3582	1362958
1998	MEAN	199146	43448	3045	157923	1726	511	285467
	STDEV	142393	66639	1363	102631	923	790	165864
	MIN	24638	0	1000	29912	305	0	31650
	MAX	863778	389829	10800	548027	6195	3473	1010679
1999	MEAN	218963	52329	3038	153616	1898	497	305141
	STDEV	199256	80005	1567	109737	1172	766	181429
	MIN	6318	0	500	26654	197	0	29100
	MAX	990659	536317	12800	575137	8076	4096	1058268
2000	MEAN	273706	49631	3091	185716	1937	551	326609
	STDEV	218054	85652	1548	141963	1318	854	192018
	MIN	20229	0	1000	29757	303	0	30810
	MAX	1175479	731407	13100	761147	11021	4020	1122885
2001	MEAN	262226	47857	3057	185937	1880	565	349966
	STDEV	206367	79674	1483	134236	1076	846	200843
	MIN	16227	0	1000	31115	199	0	34519
	MAX	1182155	672813	13100	691422	6314	3720	1172131
All Years	MEAN	208464	45938	3030	157687	1764	504	287610
	STDEV	174515	72848	1503	111135	1049	796	177040
	MIN	6318	0	500	17759	172	0	11144
	MAX	1182155	731407	20122	761147	11021	4096	1362958

Table 3.1. (Continued)

Year		*ROA, %*	*DARC*	*DARI*	*DARL*	*NFTFIR*	*INSUR, $*	*GOVT, $*	*ACRGRINC, $*	*YRSFARM, yrs*
1995	MEAN	7.56	0.59	0.30	0.43	0.23	6051.02	8993.4	237712	17.42
	STDEV	10.29	0.48	0.22	0.33	0.70	11321.09	7554.652	164977	7.43
	MIN	-30.90	0.00	0.00	0.00	-4.76	0	0	37023	1
	MAX	64.20	2.49	1.03	1.49	2.46	69988	48894	957790	37
1996	MEAN	9.48	0.63	0.30	0.44	0.21	5854.91	16982.8	260691	18.41
	STDEV	9.04	0.53	0.23	0.34	0.59	10723.56	13278.93	180012	7.43
	MIN	-11.70	0.01	0.00	0.00	-2.32	0	0	54549	2
	MAX	36.50	3.39	1.09	1.70	4.35	54993	80700	1120441	38
1997	MEAN	3.48	0.64	0.32	0.43	0.21	7956.54	15642.1	241232	19.41
	STDEV	6.18	0.47	0.27	0.36	1.23	13664.21	9688.567	156705	7.43
	MIN	-16.90	0.02	0.00	0.00	-7.75	0	0	48058	3
	MAX	16.90	2.10	1.23	2.07	5.49	89186.86	58254	833048	39
1998	MEAN	4.96	0.70	0.34	0.44	0.95	7120.22	32712.7	262834	20.41
	STDEV	6.73	0.49	0.29	0.38	5.13	19586.23	23328.77	178247	7.43
	MIN	-8.80	0.02	0.00	0.00	-2.63	0	0	55388	4
	MAX	27.60	2.71	1.26	2.38	56.26	156223	137656	882394	40
1999	MEAN	9.32	0.65	0.35	0.43	0.44	26769.1	59196	298560	21.41
	STDEV	7.05	0.41	0.30	0.35	2.43	38285.6	47224.93	206792	7.43
	MIN	-21.20	0.02	0.00	0.00	-4.30	0	0	56243	5
	MAX	34.80	1.80	1.40	1.79	27.34	176808	292493	1111095	41
2000	MEAN	9.40	0.57	0.34	0.41	0.40	16840	79900.7	344566	22.41
	STDEV	7.63	0.35	0.30	0.33	1.20	25733.45	56773.92	255417	7.43
	MIN	-11.20	0.00	0.00	0.00	-0.94	0	0	37050	6
	MAX	38.20	1.39	1.53	1.62	11.59	134906	252397	1675535	42
2001	MEAN	4.70	0.60	0.33	0.40	0.65	19105.2	61055.9	319615	23.40
	STDEV	5.83	0.39	0.29	0.31	3.30	28067	43982.75	227257	7.43
	MIN	-15.00	0.02	0.00	0.00	-3.38	0	0	46888	7
	MAX	22.80	1.69	1.44	1.46	30.22	161172	203002	1349924	43
All Farms	MEAN	6.99	0.63	0.33	0.43	0.44	12814	39212	280744	20.40769
	STDEV	8.01	0.45	0.27	0.34	2.59	24219	42673	201362	7.670737
	MIN	-30.90	0.00	0.00	0.00	-7.75	0	0	37023	1
	MAX	64.20	3.39	1.53	2.38	56.26	176808	292493	1675535	43

appropriate comparison would be farms that have similar enterprises and resources (Swenson, 2001). However, farms in the sample are not homogeneous in inputs and, especially, in outputs produced. Also, because of the small number of farms in every region, it was not possible to compare farms by region. Therefore, due to the relatively small number of farms in the analysis, their heterogeneity, and the uneven distribution between regions, the results should be interpreted with caution.

Summary

Technical and scale efficiencies and Malmquist TFP indexes and their components for panel data including 130 farms over a seven-year period (1995 to 2001) were estimated using linear programming DEA techniques. Regression models were employed to estimate the relationship between technical efficiency scores and selected farm-specific factors as well as to determine what influence technical and scale efficiencies and Malmquist TFP indexes have on farm ROA. Results are presented and discussed in Chapter IV.

CHAPTER IV. RESULTS

Introduction

This chapter consists of four sections. First, the distribution of farm technical and scale efficiency scores by each year and characteristics of efficiency scores by each region are presented and examined. Second, changes in farm productivity and its components over the time period from 1995 to 2001 are reported and discussed. Next, the relationship between farm technical efficiency scores under the assumption of constant returns-to-scale and farm-specific factors are estimated using the Tobit model. Finally, results of the OLS regression models, which were estimated in order to determine the relationship between farm financial efficiency and production performance over time, are presented and discussed.

Efficiency Scores

Farm technical efficiency (TE) scores under the assumptions of CRS and VRS and scale efficiency (SE) scores were estimated using DEA multiple-input, multiple-output models. The distributions of the scores are presented in Tables 4.1, 4.2, and 4.3. Mean, standard deviation, minimum, and maximum levels of TE and SE scores by regions are reported in Tables 4.4, 4.5, and 4.6.

TE scores under the assumption of CRS ranged from 0.05 to 1.00, with an average measure of 0.75 and standard deviation of 0.20. Therefore, output from the farms can potentially be increased by 25% if all of the farms in the sample were operating on the production frontier. It should be noted here that the minimum TE score of 0.05 appeared only once in Region 2 in 1999, with the next lowest efficiency score being 0.18.

Table 4.1. Distribution of Farm Technical Efficiency Scores: DEA CRS Output Orientation

Year	*Distribution of Farms*							
	Less than 0.40	0.40 to 0.50	0.50 to 0.60	0.60 to 0.70	0.70 to 0.80	0.80 to 0.90	0.90 to 1.00	1.00
1995	5 (4%)	11 (8%)	21 (16%)	21 (16%)	20 (15%)	17 (13%)	6 (5%)	29 (22%)
1996	8 (6%)	12 (9%)	28 (22%)	23 (18%)	15 (12%)	7 (5%)	11 (8%)	26 (20%)
1997	2 (2%)	8 (6%)	18 (14%)	13 (10%)	28 (22%)	25 (19%)	13 (10%)	23 (18%)
1998	-	3 (2%)	10 (8%)	19 (15%)	25 (19%)	28 (22%)	10 (8%)	35 (27%)
1999	20 (15%)	5 (4%)	11 (8%)	20 (15%)	19 (15%)	15 (12%)	17 (13%)	23 (18%)
2000	3 (2%)	6 (5%)	18 (14%)	24 (18%)	30 (23%)	17 (13%)	10 (8%)	22 (17%)
2001	3 (2%)	5 (4%)	10 (8%)	28 (22%)	24 (18%)	22 (17%)	16 (12%)	22 (17%)

Table 4.2. Distribution of Farm Technical Efficiency Scores: DEA VRS Output Orientation

Year	*Distribution of Farms*							
	Less than 0.40	0.40 to 0.50	0.50 to 0.60	0.60 to 0.70	0.70 to 0.80	0.80 to 0.90	0.90 to 1.00	1.00
1995	5 (4%)	9 (7%)	12 (9%)	24 (18%)	22 (17%)	12 (9%)	9 (7%)	37 (28%)
1996	4 (3%)	12 (9%)	16 (12%)	28 (22%)	21 (16%)	4 (3%)	8 (6%)	37 (28%)
1997	1 (1%)	8 (6%)	14 (11%)	12 (9%)	21 (16%)	21 (16%)	15 (12%)	38 (29%)
1998	-	3 (2%)	10 (8%)	14 (11%)	24 (18%)	25 (19%)	14 (11%)	40 (31%)
1999	18 (14%)	4 (3%)	10 (8%)	15 (12%)	21 (16%)	11 (8%)	15 (12%)	36 (28%)
2000	3 (2%)	4 (3%)	8 (6%)	28 (22%)	24 (18%)	16 (12%)	14 (11%)	33 (25%)
2001	2 (2%)	4 (3%)	9 (7%)	20 (15%)	23 (18%)	20 (15%)	18 (14%)	34 (26%)

Table 4.3. Distribution of Farm Scale Efficiency Scores: DEA Output Orientation

Year	*Distribution of Farms*							
	Less than 0.70	0.70 to 0.75	0.75 to 0.80	0.80 to 0.85	0.85 to 0.90	0.90 to 0.95	0.95 to 1.00	1.00
1995	1 (1%)	2 (2%)	2 (2%)	4 (3%)	4 (3%)	20 (15%)	45 (35%)	52 (40%)
1996	1 (1%)	1 (1%)	3 (2%)	5 (4%)	8 (6%)	21 (16%)	43 (33%)	48 (37%)
1997	4 (3%)	-	4 (3%)	5 (4%)	5 (4%)	10 (8%)	56 (43%)	46 (35%)
1998	2 (2%)	-	1 (1%)	-	3 (2%)	11 (8%)	48 (37%)	65 (50%)
1999	3 (2%)	1 (1%)	-	3 (2%)	5 (4%)	16 (12%)	55 (42%)	47 (36%)
2000	2 (2%)	2 (2%)	-	-	18 (14%)	20 (15%)	56 (43%)	29 (22%)
2001	1 (1%)	1 (1%)	1 (1%)	4 (3%)	10 (8%)	20 (15%)	53 (41%)	40 (31%)

From Table 4.1, it follows that the number of technically efficient farms (i.e., farms operating on the production frontier) under the assumption of CRS fell to 22 (17%) in 2000 and 2001 from 35 (27%) in 1998. While 45% to 75% of the farms exhibited TE scores higher than 0.70, only 2% to 6% of the farms had TE scores lower than 0.40 with the exception of 1999, when 15% of the farms had TE scores less than 0.40. Most of those farms (15 out of 20) were located in Region 2. The probable reason for such low scores in 1999 was that farmers could not get into the fields during the planting season and, therefore, took the preventive planting insurance payments, which are not accounted for in measuring farm efficiency and productivity.

Table 4.4. Technical Efficiency Scores by Regions: DEA CRS Output Orientation

		1995	*1996*	*1997*	*1998*	*1999*	*2000*	*2001*	*Average*
Region 1	Mean	0.88	0.86	0.87	0.87	0.88	0.82	0.87	0.86
(N = 26)	SD	0.14	0.15	0.13	0.11	0.09	0.13	0.11	0.13
	Min	0.59	0.56	0.53	0.61	0.71	0.52	0.64	0.57
	Max	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Region 2	Mean	0.67	0.62	0.69	0.75	0.55	0.66	0.71	0.66
(N = 43)	SD	0.15	0.18	0.15	0.15	0.28	0.18	0.18	0.18
	Min	0.45	0.32	0.40	0.41	0.05	0.23	0.28	0.31
	Max	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Region 3	Mean	0.67	0.67	0.72	0.85	0.76	0.76	0.75	0.74
(N = 39)	SD	0.24	0.20	0.19	0.17	0.21	0.18	0.17	0.20
	Min	0.25	0.35	0.24	0.44	0.28	0.45	0.43	0.33
	Max	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Region 4	Mean	0.79	0.76	0.86	0.80	0.75	0.80	0.82	0.79
(N = 22)	SD	0.18	0.21	0.18	0.17	0.25	0.17	0.16	0.19
	Min	0.45	0.39	0.45	0.50	0.18	0.49	0.43	0.41
	Max	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Average		0.73	0.71	0.76	0.81	0.71	0.75	0.77	0.75
SD		0.20	0.21	0.18	0.16	0.25	0.18	0.17	0.20
Median		0.73	0.66	0.76	0.82	0.76	0.75	0.77	0.76
Mode		1.00	1.00	1.00	1.00	1.00	1.00	1.00	N/A
Minimum		0.25	0.32	0.24	0.41	0.05	0.23	0.28	0.05
Maximum		1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Analyzing TE scores by regions (Table 4.4), it can be seen that Regions 1 and 4 had the highest mean levels of TE scores with Region 1 having the highest mean scores every year, while average standard deviation of TE scores varied from 0.13 in Region 1 to 0.18-0.20 in all other regions during the period from 1995 to 2001. Average technical efficiency scores under the assumption of constant returns-to-scale (TESCRS) vary from 0.55 in 1999 in Region 2 to 0.88 in Region 1 in 1995 and 1999. With the exclusion of 1999 from the analysis, the range goes from 0.62 for Region 2 in 1996 to 0.88 in Region 1 in 1995 and 1999. These results for TESCRS indicate the existence of potential gains from improving technical efficiency for farms in the sample, especially for the farms in Regions 2 and 3.

TE scores under the assumption of variable returns-to-scale (TESVRS) are just slightly higher than TESCRS scores (Tables 4.2 and 4.5). These results suggest that no

Table 4.5. Technical Efficiency Scores by Regions: DEA VRS Output Orientation

		1995	*1996*	*1997*	*1998*	*1999*	*2000*	*2001*	*Average*
Region 1	Mean	0.90	0.88	0.90	0.90	0.91	0.86	0.89	0.89
(N = 26)	SD	0.14	0.15	0.13	0.10	0.10	0.12	0.11	0.12
	Min	0.60	0.57	0.53	0.63	0.75	0.54	0.65	0.60
	Max	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Region 2	Mean	0.71	0.66	0.73	0.77	0.61	0.70	0.75	0.70
(N = 43)	SD	0.17	0.18	0.17	0.15	0.27	0.19	0.19	0.19
	Min	0.47	0.34	0.41	0.43	0.06	0.24	0.28	0.33
	Max	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Region 3	Mean	0.71	0.71	0.79	0.85	0.79	0.81	0.80	0.78
(N = 39)	SD	0.24	0.21	0.19	0.17	0.21	0.17	0.18	0.20
	Min	0.28	0.37	0.39	0.46	0.29	0.48	0.45	0.38
	Max	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Region 4	Mean	0.82	0.79	0.88	0.84	0.77	0.85	0.86	0.83
(N = 22)	SD	0.18	0.20	0.16	0.18	0.25	0.16	0.15	0.19
	Min	0.46	0.40	0.46	0.51	0.21	0.50	0.44	0.42
	Max	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Average		0.77	0.74	0.81	0.83	0.75	0.79	0.81	0.79
SD		0.20	0.21	0.18	0.16	0.25	0.18	0.17	0.20
Median		0.75	0.72	0.83	0.85	0.78	0.79	0.83	0.80
Mode		1.00	1.00	1.00	1.00	1.00	1.00	1.00	N/A
Minimum		0.28	0.34	0.39	0.43	0.06	0.24	0.28	0.08
Maximum		1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

significant economies of scale should be present among farms in the sample. Between 25% and 31% of the farms were technically efficient under VRS, while 54% to 79% of the farms exhibited TESVRS scores higher than 0.70, and only 1% to 4% (again with the exception of 1999) of the farms had scores less than 0.40.

Scale efficiency (SE) varied from 0.08 to 1.00 over the whole time period with an average measure of 0.96 and standard deviation of 0.08 (Table 4.6). Over the whole period, 90% to 95% of the observations exhibited scale measures greater than 0.85, and only 1% to 2% of the farms had SE scores less than 0.70 during all years (Table 4.3). The percentage of scale efficient farms tends to be high: 22% to 50% of the farms were fully scale efficient, and 65% to 87% of the farms had TE scores higher than 0.95 during 1995 to 2001.

Table 4.6. Scale Efficiency Scores by Regions: DEA Output Orientation

		1995	*1996*	*1997*	*1998*	*1999*	*2000*	*2001*	*Average*
Region 1	Mean	0.98	0.98	0.96	0.97	0.97	0.95	0.98	0.97
(N = 26)	SD	0.04	0.05	0.07	0.04	0.05	0.06	0.04	0.05
	Min	0.82	0.81	0.76	0.86	0.85	0.80	0.86	0.82
	Max	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Region 2	Mean	0.95	0.95	0.95	0.97	0.94	0.95	0.95	0.95
(N = 43)	SD	0.07	0.06	0.08	0.05	0.18	0.09	0.06	0.09
	Min	0.71	0.72	0.63	0.69	0.08	0.44	0.72	0.55
	Max	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Region 3	Mean	0.96	0.94	0.93	0.99	0.96	0.94	0.95	0.95
(N = 39)	SD	0.07	0.08	0.14	0.03	0.06	0.07	0.06	0.08
	Min	0.69	0.65	0.24	0.88	0.74	0.74	0.83	0.66
	Max	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Region 4	Mean	0.97	0.96	0.98	0.96	0.96	0.95	0.96	0.96
(N = 22)	SD	0.04	0.06	0.04	0.08	0.07	0.10	0.08	0.06
	Min	0.86	0.76	0.84	0.68	0.69	0.54	0.63	0.73
	Max	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Average		0.96	0.95	0.95	0.98	0.95	0.94	0.96	0.96
Conditional Average*		0.96	0.95	0.93	0.98	0.93	0.94	0.94	0.95
SD		0.06	0.07	0.10	0.05	0.12	0.08	0.06	0.08
Median		0.99	0.98	0.99	1.00	0.99	0.97	0.97	0.99
Mode		1.00	1.00	1.00	1.00	1.00	1.00	1.00	N/A
Minimum		0.69	0.65	0.24	0.68	0.08	0.44	0.63	0.08
Maximum		1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

* Conditional Average is average SE scores calculated for the farms that are technically efficient under the VRS model, but do not lie on the production frontier under the CRS model.

Following Banker and Thrall (1992), conditional average SE scores were calculated to see if obtained returns-to-scale were confounded with technical inefficiency. Only farms that are technically efficient under the VRS model, but do not lie on the production frontier under the CRS model, were included into calculation of conditional average SE scores. Results indicate that conditional average scores are similar to average scores, and equality of the means between two scores could not be rejected in any year.

Analysis of SE scores by regions indicates that mean SE scores varied from 0.95 to 0.97 over all years, with average standard deviation varying from 0.05 in Region 1 to 0.09 in Region 2. Among the regions, Region 3 had the lowest score of 0.93 in 1997 as well as the highest score of 0.99 in 1998. These results indicate that most farms operate at an efficient scale and, therefore, no significant improvements in scale efficiency can be accomplished by most farms in the sample by changing the scale of their operation. Further, to examine differences in the estimated efficiency ratios between the regions, Levene's tests for homogeneity of mean variances of TECRS, TEVRS, and SE scores between the regions for each year were performed in SAS. Levene's test (Levene, 1960), which is widely considered to be the standard homogeneity of variance test, has the dispersion-variable-ANOVA form, where the dispersion variable is computed as

$$\chi_{ij}^2 = (y_{ij} - \bar{y}_i)^2 , \tag{4.1}$$

where χ is the dispersion variable, *i* and *j* are the indexes of the regions, and *y* corresponds to the efficiency scores.

The results should be interpreted with caution since the number of farms is different in each region, and this fact could cause some problems with comparison. The results of the tests are reported in Tables 4.7, 4.8, and 4.9 using Duncan grouping, where the same letter by the regions indicates that the mean efficiency scores of those regions are not significantly different. The results of the F-tests show that the equality of means for all four regions for TESCRS is rejected at the 1% significance level for 1995 and 1999 and at the 10% significance level in 1998 and 2001. For TESVRS, the equality of the means is rejected at the 1% significance level in 1995 and 1999 and at the 10% significance level in all other years except for 1997.

Table 4.7. Levene's Test for Homogeneity of Mean Variances of TESCRS between the Regions

Region	*1995****		*1996*		*1997*		*1998**		*1999****		*2000*		*2001*	
	Mean	Letter+	Mean	Letter	Mean	Letter	Mean	Letter	Mean	Letter	Mean	Letter	Mean	Letter
1	0.88	A	0.86	A	0.87	A	0.87	A	0.88	A	0.82	A	0.87	A
2	0.67	B	0.62	C	0.69	B	0.75	B	0.55	C	0.66	B	0.71	C
3	0.67	B	0.67	C	0.72	B	0.85	A	0.76	B	0.76	A	0.75	BC
4	0.79	A	0.76	B	0.86	A	0.80	AB	0.75	B	0.80	A	0.82	AB

+ Means with the same letter are not significantly different.
*** Overall homogeneity of variance among all regions can be rejected at 1% level.
** Overall homogeneity of variance among all regions can be rejected at 5% level.
* Overall homogeneity of variance among all regions can be rejected at 10% level.

Table 4.8. Levene's Test for Homogeneity of Mean Variances of TESVRS between the Regions

Region	*1995****		*1996**		*1997*		*1998***		*1999****		*2000**		*2001**	
	Mean	Letter+	Mean	Letter	Mean	Letter	Mean	Letter	Mean	Letter	Mean	Letter	Mean	Letter
1	0.896	A	0.88	A	0.90	A	0.897	A	0.90	A	0.86	A	0.89	A
2	0.71	B	0.66	C	0.73	C	0.77	B	0.61	C	0.70	B	0.75	C
3	0.71	B	0.71	BC	0.79	BC	0.85	A	0.79	B	0.80	A	0.80	BC
4	0.82	A	0.79	AB	0.88	AB	0.84	AB	0.77	B	0.85	A	0.86	AB

+ Means with the same letter are not significantly different.
*** Overall homogeneity of variance among all regions can be rejected at 1% level.
** Overall homogeneity of variance among all regions can be rejected at 5% level.
* Overall homogeneity of variance among all regions can be rejected at 10% level.

Table 4.9. Levene's Test for Homogeneity of Mean Variances of SCEFF between the Regions

Region	*1995*		*1996*		*1997*		*1998*		*1999*		*2000*		*2001*	
	Mean	Letter[+]	Mean	Letter	Mean	Letter	Mean	Letter	Mean	Letter	Mean	Letter	Mean	Letter
1	0.977	A	0.976	A	0.959	A	0.973	A	0.969	A	0.948	A	0.975	A
2	0.946	A	0.946	A	0.955	A	0.974	A	0.935	A	0.937	A	0.952	A
3	0.956	A	0.940	A	0.929	A	0.986	A	0.959	A	0.947	A	0.945	A
4	0.968	A	0.960	A	0.976	A	0.964	A	0.959	A	0.948	A	0.959	A

[+] Means with the same letter are not significantly different.

*** Overall homogeneity of variance among all regions can be rejected at 1% level.

** Overall homogeneity of variance among all regions can be rejected at 5% level.

* Overall homogeneity of variance among all regions can be rejected at 10% level.

The results for each region indicate that Region 1 always has better average TE scores estimated under the assumptions of CRS and VRS than Region 2, better TE scores than Region 3 during all years but 1998 and 2000, and better mean TE scores than Region 4 in 1996 and 1999. However, inability to reject the hypothesis of difference in mean TE scores between Regions 1 and 4 in 1995, 1998, and 2001 could be due to the fact that these regions do not have a sufficient number of farms in the analysis (Region 1 has 26 farms, region 4 has 22 farms, while Regions 2 and 3 have 43 and 39 farms, respectively). Region 2 had the lowest average statistically significant TE scores as compared to all other regions in 1999 and 2000, while there was no statistically significant difference in TE scores between Regions 2 and 3 in all other years except for 1998.

Equality of the means could not be rejected in any year for SCEFF. This result indicates that average SE scores are statistically similar among all of the regions. Spearman Rank Correlation Coefficients (SRCC) tests were conducted to evaluate if there is statistical evidence of a stochastic pattern and commonness in TE scores among each of the years among the farms in the data set. The SRCC can range from values of –1 to +1, where values of –1 indicate perfect negative correlation and values of +1 indicate perfect positive correlation. Correlations of zero indicate that the farms TE scores are not related to each other among the years under consideration.

Spearman rank-order correlation is a nonparametric measure of association based on the rank of the data values. The formula is

$$\rho = \frac{\sum (R_k - \overline{R})(S_k - \overline{S})}{\sqrt{(R_k - \overline{R})^2 (S_k - \overline{S})^2}}, \tag{4.2}$$

where ρ is a correlation coefficient between farm ranks in years *t* and *t+1*; R_k is the rank of the *k*-th farm in year *t*, S_k is the rank of the *k*-th farm in year *t+1*, $\overline{R}$ is the mean of the R_k values, and $\overline{S}$ is the mean of the S_k values. Spearman's correlation was computed in SAS by ranking the data and using the ranks in the Pearson product-moment correlation formula. In case of ties, the averaged ranks are used (SAS/STAT User's Guide, 1999).

The results are presented in Table 4.10. Results indicate that correlation between ranks across the years is positive and statistically significant at the 1% level. As expected, the highest correlation values are between years that follow each other, and the lowest is between the years that are furthest apart. However, the overall correlation coefficients are relatively high. All are higher than 0.45, and three of them exceed 0.70, with correlation between 1995 and 1996 being almost 0.80. These results together with statistical significance at the 1% level indicate that farms maintain their relative position to the production frontier as compared to other farms, not only on a year-to-year basis, but also over longer period of time as well.

Table 4.10. Spearman Rank Correlation Coefficient Estimates for TECRS Scores

Year	*1995*	*1996*	*1997*	*1998*	*1999*	*2000*
1996	0.7962					
	<.0001					
1997	0.6578	0.7152				
	<.0001	<.0001				
1998	0.5267	0.5862	0.6062			
	<.0001	<.0001	<.0001			
1999	0.5890	0.6579	0.6761	0.7491		
	<.0001	<.0001	<.0001	<.0001		
2000	0.6063	0.6105	0.6363	0.6272	0.6739	
	<.0001	<.0001	<.0001	<.0001	<.0001	
2001	0.4644	0.4557	0.5818	0.4975	0.5439	0.6736
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001

Notes: Top number is test statistic; bottom number is two-tailed level of significance.

Malmquist TFP Indexes

Changes in average farm productivity and its components for all farms in the data set and for each region are reported in Table 4.11. The cumulative change of Malmquist TFP indexes and its components for the whole data set is depicted in Figure 4.1 and in Figures 4.3-4.6 for each region, while the cumulative change of Malmquist TFP indexes by regions is shown in Figure 4.2. The results for each individual farm are reported in Appendix C.

The results presented in Table 4.11 and Figure 4.1 indicate that over the 1995 to 2001 time period, there has been moderate productivity growth of approximately 1.7% per year, which was mostly attributed to technical change. Changes in technical efficiency had a very small effect on TFP.

These results are similar to those reported by Zofio and Lovell (2001), who reported average productivity growth of 2.11% per year for all North Dakota farms during the period from 1960 to 1990. They also found that almost all of the productivity change was attributed to technical progress. However, Malmquist TFP changes and its components vary significantly from year to year. There was sharp growth in Malmquist TFP of 16% in 2000, moderate growth of 1.7% in 1998 and 1999, and declines of 5% in 1996 and 2001.

From Table 4.11 and Figure 4.1, it follows that the result of such variation is attributed to both TECHCH and EFFCH contributions to TFP. Both factors exhibited volatile changes and offset each other in 1997, 1998, and 1999, while moving in the same direction in all other years.

Table 4.11. Changes in Average Farm Productivity and Its Components

	Time Period	*Malmquist Index (MALMQTFP)*	*Technical Change (TECHCH)*	*Efficiency Change (EFFCH)*	*Pure Efficiency Change (PEFFCH)*	*Scale Change (SCCH)*
Region 1	95 – 96	0.9498	0.9683	0.9814	0.9837	0.9976
	96 – 97	0.9630	0.9537	1.0102	1.0269	0.9828
	97 – 98	0.8761	0.8654	1.0139	0.9980	1.0155
	98 – 99	1.3136	1.3029	1.0089	1.0133	0.9954
	99 – 00	0.9508	1.0286	0.9252	0.9463	0.9766
	00 – 01	1.0424	0.9800	1.0656	1.0347	1.0299
	Mean	1.0071	1.0081	1.0000	1.0000	0.9995
Region 2	95 – 96	0.9019	0.9944	0.9060	0.9059	1.0014
	96 – 97	1.0345	0.9148	1.1315	1.1240	1.0058
	97 – 98	1.0670	0.9785	1.0912	1.0655	1.0235
	98 – 99	0.8062	1.2864	0.6272	0.6918	0.9054
	99 – 00	1.3875	1.1257	1.2333	1.2193	1.1273
	00 – 01	0.9654	0.8993	1.0729	1.0637	1.0072
	Mean	1.0121	1.0249	0.9877	0.9955	1.0097
Region 3	95 – 96	1.0143	1.0010	1.0130	1.0340	0.9803
	96 – 97	0.9417	0.8611	1.0936	1.1226	0.9732
	97 – 98	1.1571	0.9776	1.1847	1.0941	1.0825
	98 – 99	1.0589	1.2075	0.8772	0.9039	0.9707
	99 – 00	1.1259	1.1080	1.0151	1.0406	0.9749
	00 – 01	0.8944	0.8977	0.9976	0.9867	1.0104
	Mean	1.0278	1.0020	1.0259	1.0278	0.9979
Region 4	95 – 96	0.9699	1.0186	0.9530	0.9626	0.9912
	96 – 97	1.1010	0.9685	1.1369	1.1164	1.0192
	97 – 98	0.8793	0.9405	0.9348	0.9504	0.9846
	98 – 99	1.1049	1.2521	0.8836	0.8864	0.9959
	99 – 00	1.1132	0.9803	1.1353	1.1549	0.9831
	00 – 01	0.9748	0.9450	1.0312	1.0152	1.0156
	Mean	1.0200	1.0123	1.0078	1.0100	0.9982
All Farms	95 – 96	0.9556	0.9951	0.9601	0.9681	0.9925
	96 – 97	1.0020	0.9147	1.0958	1.1022	0.9936
	97 – 98	1.0171	0.9481	1.0737	1.0398	1.0324
	98 – 99	1.0175	1.2596	0.8083	0.8437	0.9575
	99 – 00	1.1641	1.0749	1.0830	1.0951	1.0247
	00 – 01	0.9597	0.9221	1.0413	1.0261	1.0141
	Mean	1.0171	1.0125	1.0049	1.0085	1.0022

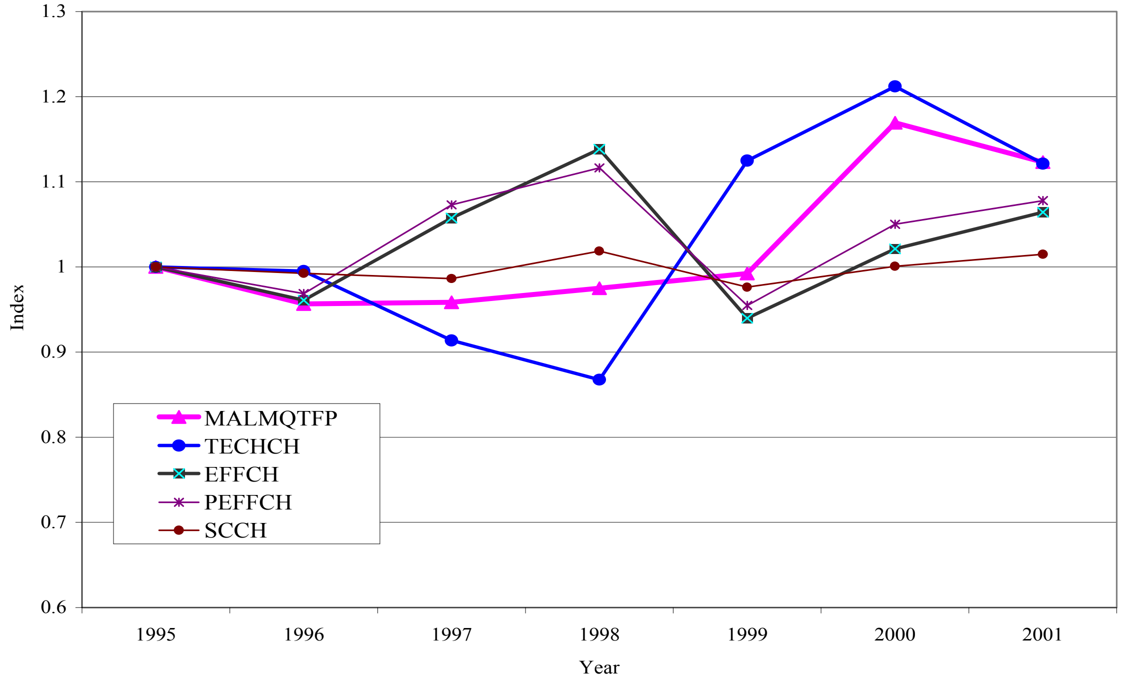

Figure 4.1. Cumulative change of Malmquist TFP index and its components, all regions, 1995-2001

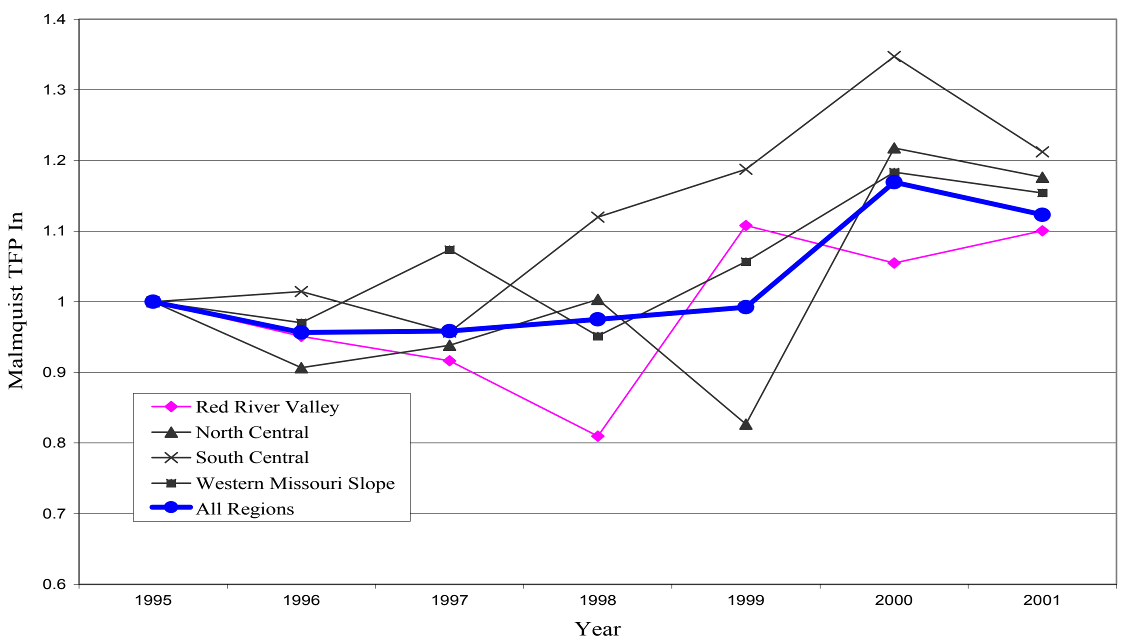

Figure 4.2. Cumulative change of Malmquist TFP indexes by region, 1995-2001

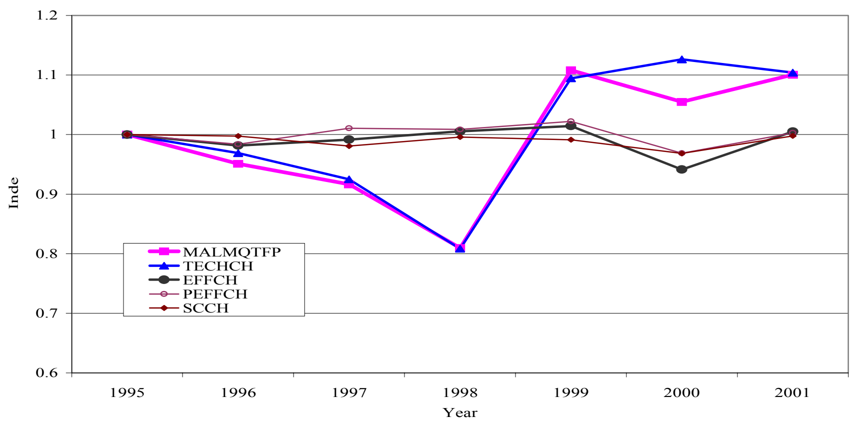

Figure 4.3. Cumulative change of Malmquist TFP index and its components, Region 1, Red River Valley

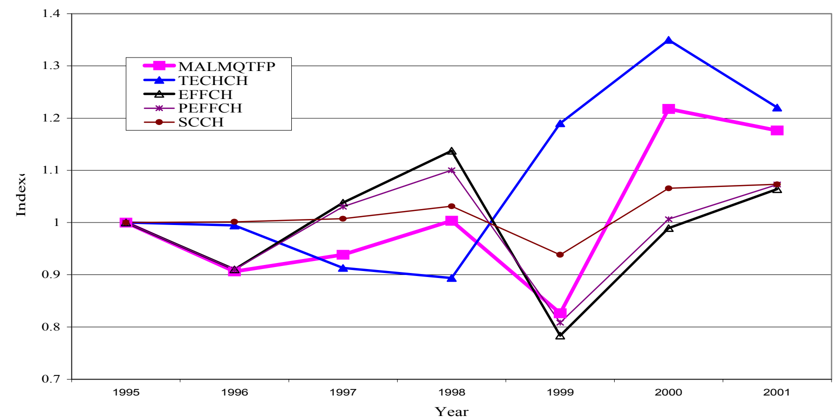

Figure 4.4. Cumulative change of Malmquist TFP index and its components, Region 2, North Central

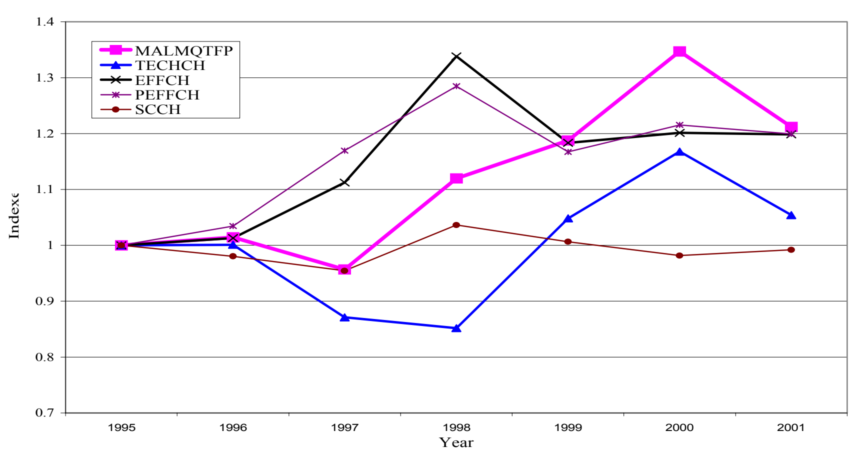

Figure 4.5. Cumulative change of Malmquist TFP index and its components, Region 3, South Central

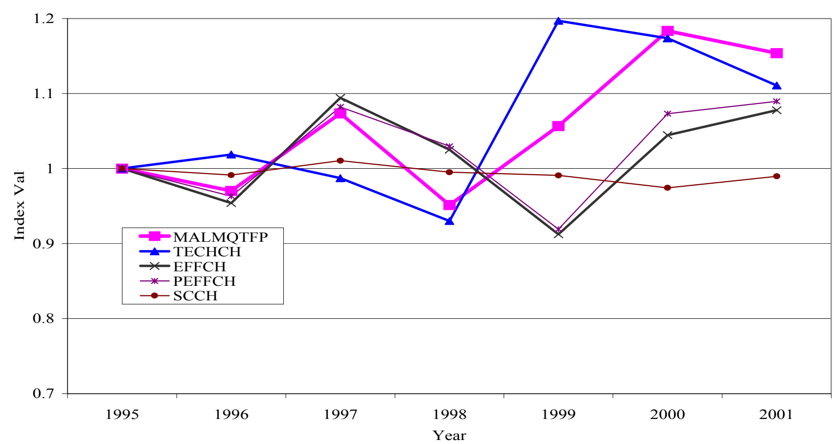

Figure 4.6. Cumulative change of Malmquist TFP index and its components, Region 4, Western Missouri Slope

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Over the seven-year time period, technical change grew at a mean rate of 1.25% for all farms in the data set. However, growth has not been steady. Table 4.11 indicates that all regions experienced similar patterns in TECHCH. There was little technical change in 1996, technical progress in 1999 and 2000, and technical regress in 1997, 1998, and 2001. Patterns of TECHCH are the same in Regions 2 and 3 during all of the years. Farms in Region 1 in 1996 exhibited technical regress of 3.17%. In Region 4, farms exhibited technical regress of 2% in 2000.

In contrast to TECHCH, although there has been no overall change in efficiency, farms generally improved their resource allocation during all years but 1996 and 1999. In terms of EFFCH, farm movements towards and away from the production frontier were attributed to pure efficiency change (PEFFCH). Changes in scale change (SCCH) did not exceed 1-3% per year with the exception of 1999, when SCCH fell 4%. However, this fall was mostly attributed to Region 2, where a lot of farmers experienced a wet season and could not plant their crops, thus receiving preventative planting insurance payments. That, in turn, significantly lowered their PEFFCH scores and had a big impact on average scores for the whole sample.

The absence of an apparent trend in the EFFCH and, consequently, in the Malmquist TFP index might be explained by farms in the sample producing different output mixes using different inputs as well as facing dissimilar agro-climatic conditions. This conclusion is supported by results from Table 4.11 and Figure 4.2, which depict different patterns for Malmquist TFP indexes among the regions. For example, Malmquist TFP indexes moved in the same direction between Regions 1 and 4, 2 and 3, and 3 and 4 only three years out of six, and between Regions 2 and 4 for four years out of six. TFP changes for Region 1 differ from all other regions because this Region differs significantly from the others in output mix (e.g., no farms in Region 1 were classified as mixed or livestock farms in any year).

Turning to the analysis of cumulative yearly changes in TFP and its components in each Region (Figures 4.3-4.6), it can be seen that in Region 1, changes in TFP are mostly attributed to TECHCH, while EFFCH had no significant impact on TFP in any year except for 2000. However, over the seven-year period, there have been no changes in either of the productivity factors in Region 1. The trend in all other regions is more striking. Each one of those regions experienced mean productivity growth of 1.2% to 2.7% per year as a result of mixed and often offsetting impacts of TECHCH and EFFCH.

Except for TECHCH, another similar pattern for all regions is an absence of noticeable changes in farm location relative to the scale frontier, except for Region 2 in 1999 because of extremely adverse weather conditions.

These results may be due to several factors. TE is measured in terms of a farmer's ability to produce the maximum amount of output for a given level of inputs, while productivity change is a ratio of farm outputs to its inputs between two time periods. However, there are more factors involved in a farmer's decisions of what outputs to produce and inputs to use. A farmer makes his decisions ex ante, while efficiency and productivity are measured ex post. Market prices, governmental payments, credit constraints, and anticipated weather conditions play essential roles in a farmer's production decisions, while those factors are not included or accounted for in the measures of efficiency and productivity scores. Those factors may have even larger effects when farms are not homogeneous in output production and input usage, as was the case in this research.

Technical Efficiency and Farm-Specific Factors

Table 4.12 reports the results of a Tobit analysis which was used to estimate the relationship between technical efficiency under the assumption of CRS and selected farm-specific characteristics. Information in the table includes parameter estimates, standard errors, Chi-square statistics, and p-values.

Chi-square statistics are calculated using Wald tests, which test the null hypothesis that a parameter is 0, which means that the corresponding variable has no effect on the dependent variable given that the other variables are in the model. This statistic is computed as a quadratic form in the appropriate parameter estimates using the corresponding sub-matrix of the asymptotic covariance matrix estimate. The asymptotic covariance matrix is computed as the inverse of the observed information matrix (SAS/STAT User's Guide, 1999).

Results indicate that group and time effects are significant at the 1% level. Region 1 is shown to outperform all other regions in resource allocation, which coincides with results from Tables 4.4 and 4.7. Also, farms had lower TE scores in 1995, 1996, 1999, and 2000, and slightly higher TE scores in 1998 as compared to 2001; the results were significant at the 10% level.

Variables FTYPE are significant for all types of farms at the 1% level. Livestock farms are shown to be the most technically efficient and mixed farms more efficient than crop farms. This result contradicts the initial hypothesis, introduced in Chapter 3, that crop farms should have been the most efficient and livestock farms the least efficient, as technical efficiency is assumed to be correlated with financial performance.

Table 4.12. Relationship between Efficiency and Farm Characteristics, Tobit Model

Explanatory Variable	*Estimate*	*Standard Error*	*Chi-Square*	*Pr > ChiSq*
INTERCEPT	0.7543	0.0282	717.16	<.0001
REGION 1	0.1300	0.0192	45.71	<.0001
REGION 2	-0.0231	0.0156	2.20	0.1381
REGION 3	0.0403	0.0164	6.05	0.0139
REGION 4	0.0000	0.0000	.	.
YEAR, 1995	-0.0525	0.0209	6.31	0.0120
YEAR, 1996	-0.0797	0.0202	15.48	<.0001
YEAR, 1997	-0.0142	0.0200	0.51	0.4763
YEAR, 1998	0.0348	0.0189	3.40	0.0654
YEAR, 1999	-0.0319	0.0181	3.11	0.0778
YEAR, 2000	-0.0461	0.0183	6.36	0.0117
YEAR, 2001	0.0000	0.0000	.	.
FTYPE, 1	-0.0655	0.0156	17.56	<.0001
FTYPE, 2	0.1435	0.0187	59.09	<.0001
FTYPE, 3	0.0000	0.0000	.	.
DARC	-0.0853	0.0129	43.46	<.0001
DARI	-0.0071	0.0213	0.11	0.7400
DARL	0.0795	0.0159	25.07	<.0001
NFTFIR	-0.0040	0.0019	4.33	0.0374
YRSFARM	-0.0008	0.0007	1.29	0.2566
INSUR	-0.0024	0.0002	117.75	<.0001
GOVT	-0.0000	0.0002	0.01	0.9140
ACRGRINC	0.0312	0.0038	66.04	<.0001
SCALE	0.1442	0.0034		
N	130			
Log Likelihood Function	471.18			

The following reasons might explain these contradictory results. First, more adverse events have affected crop production than livestock enterprises during the 1995 to 2001 time period. Increased amounts of insurance payments during 1999 to 2001 and government disaster payments in 1998 to 2001 (see Table 3.1) were attributed to crop production. Second, additional government payments were made in 1998 to 2001 to offset lower market prices for certain crops. Those payments improved the financial results of crop farmers, though inputs used per unit value of output were greater for crop than for livestock producers. However, it is not clear whether crop farmers have lower technical efficiency scores because they are truly less efficient in allocating their resources, because of adverse events affecting their production, or some combination of both reasons.

Leverage variables DARC and DARL (current and long-term debt-to-asset ratios) were statistically significant at the 1% level, while variable DARI (intermediate debt-to-asset ratio) was not significant. Therefore, the results for DARI are consistent with the perfect market hypothesis, under which the efficiency level of the farm should not be influenced by any of the leverage ratios. The results do not support the agency cost and credit evaluation concepts of finance theory.

Variable DARC has a negative influence on TE. The result contradicts the free cash flow concept and, at the same time, supports the agency cost concept in finance. Perhaps technically inefficient farmers cannot generate enough financial resources to cover their operating expenses. Being unable to allocate resources efficiently, they are forced to borrow more money. At the same time, lenders impose a higher proportion of bonding (collateral) and adverse incentive (higher interest rates and servicing fees) costs on those producers which, in turn, lowers their TE.

Variable DARL has a positive influence on TE. This relationship is consistent with the credit evaluation concept, consequently indicating that bankers prefer to finance more efficient farmers. It is also consistent with the liquidity preference theory of credit use in agriculture, developed by Baker (1968) and extended by Barry et al. (1981). The liquidity preference theory suggests that lenders are more willing to finance producers with high repayment capacity and, in order to attract them, offer favorable financing terms.

Following Chavas and Aliber (1993), another explanatory reason for the positive influence of DARL on TE could be because technical progress is embodied in long-term assets in agriculture. In order to become more technically efficient, a farmer has to acquire new long-term assets, and since such purchases are usually financed, at least partially, it causes debt to increase.

As expected, the non-farm to total farm income ratio (NFTFIR) variable has a negative impact on TE and is significant at the 5% level. This result indicates that part-time farmers are less efficient in utilizing the measured resources than their full-time peers. The result conflicts with findings of Chavas and Aliber (1993), who found no significant relationship between NFTFIR and TE.

The variable YRSFARM was not significant. Therefore, this analysis does not provide evidence that farming experience has an effect on a producer's ability to allocate resources more or less efficiently. These results could be due to the fact that although older producers have more experience, yet they may be more conservative in adopting innovating practices than younger farmers.

The INSUR variable is negatively correlated with TE, and it is significant at the 1% level. This result supports the hypothesis that lower TE scores for farms that experienced adverse conditions are offset by compensating insurance payments.

Variable GOVT has an expected sign, but it is not statistically significant. This result could be obtained because of the reason that government payments are received mostly by crop farmers. Since the analysis is conducted for all types of farms, absence or small amounts of government payments paid to the livestock and mixed producers did not allow establishing a strong relationship between GOVT and TE, as might be expected for the crop farms.

The accrual gross income (ACRGRINC) variable is found to have a positive effect on TE and is significant at the 1% level. This result indicates there is an important difference in TE of farms by size and that large farms are technically more efficient in this group than small farms.

Efficiency, Productivity, and Profitability

Depending on the possible structures of the error components, panel data models can be estimated as

1) Fixed or random effect models. The model is referred to as the fixed effects model if it has a specific intercept for each of the cross sectional groups (the effects are nonrandom). The model is referred to as the random effects model if there is still a group-specific disturbance, but only an identical single draw enters the regression in each period (Greene, 1997);
2) One-way or two-way effect models. In one-way effects, the specification of the model is dependent only on the cross section to which the observation belongs. In the two-way effects model, both cross section and the time-specific effects enter the model;
3) First-order heteroscedastic autoregressive models with contemporaneous correlation between cross sections; and
4) Mixed variance-component moving average error models (SAS/STAT User's Guide, 1999).

As a result, six different econometric models (fixed one, random one, fixed two, random two, first-order autoregressive, and mixed variance-component moving average error) were estimated in order to examine how profitability of individual farms is related to their technical and scale efficiency and to determine if changes in farm productivity have an impact on a farm's financial performance. *F* tests were conducted to test the linear hypotheses about the regression parameters. Results of the tests indicated that the linear hypotheses about the regression parameters could not be rejected at the 1% level in any of the econometric models estimated.

F tests for both one-way and two-way effect models were conducted as a specification test for the hypothesis that fixed effects parameters equal zero. Results reject the null hypothesis of no fixed effects at the 1% level in both one- and two-way effect models.

Finally, Hausman's (Hausman and Taylor, 1982) *m*-statistics tests were conducted as a specification test for random effects. Results indicated that the null hypothesis about the presence of random effects could not be rejected at the 1% level in both one-way and two-way effect models.

Tables 4.13 and 4.14 provide the results of the econometric models estimating the relationship between ROA and technical and scale efficiencies, and ROA and the Malmquist TFP indexes. Since none of the tests allowed us to reject the linear hypotheses about the regression parameters at the 1% level in any of the econometric models, all four models (excluding one-way fixed and one-way random effect models) are presented here. The two-way random effects model was estimated using the method of Fuller and Battese (1974); the mixed variance-component moving average error model was estimated using

Table 4.13. Relationship between ROA and Efficiency Scores

Explanatory Variable	Econometric Model: Random Two (Fuller-Battese)				Mixed Variance-Component Moving Average (Da Silva)			
	Estimate	Standard Error	t-Value*	Pr >| t |**	Estimate	Standard Error	t-Value*	Pr >| t |**
Intercept	-8.2333	3.3224	-2.48	0.0134	-8.5783	3.3841	-2.53	0.0114
TESCRS	11.1204	1.5097	7.37	<0.0001	11.2580	1.5430	7.30	<0.0001
SCEFF	7.0671	3.3506	2.11	0.0352	7.3197	3.4302	2.13	0.0332
R^2	0.0885				0.0888			
F Test***								
Hausman Test****			2.11	0.3485				
F Test*****			37.72	0.0001			37.44	0.0001

Explanatory Variable	Econometric Model: Fixed Two				First-Order Autoregressive (Parks)			
	Estimate	Standard Error	t-Value*	Pr >| t |**	Estimate	Standard Error	t-Value*	Pr >| t |**
Intercept					-21.0730	6.2989	-3.35	0.0009
TESCRS	12.0412	1.9121	6.30	<0.0001	6.2545	2.5080	2.49	0.0128
SCEFF	4.2658	3.8854	1.10	0.2727	24.1072	6.8198	3.53	0.0004
R^2	0.7387				0.5182			
F Test***			4.58	<0.0001				
Hausman Test****								
F Test*****			25.32	0.0001			16.23	0.0001

* F value for F test for no fixed effects and F test of linear hypotheses about the regression parameters, m value for Hausman test for random effects.
** Pr > | F | for F test for no fixed effects and F test of linear hypotheses about the regression parameters, Pr > | m | value for Hausman test for random effects.
*** Test for no fixed effects.
**** Test for Random effects.
***** Test of linear hypotheses about the regression parameters.

Table 4.14. Relationship between ROA and Malmquist TFP

Explanatory Variable	Econometric Model							
	Random Two (Fuller-Battese)				Mixed Variance-Component Moving Average (Da Silva)			
	Estimate	Standard Error	t-Value*	Pr >| t |**	Estimate	Standard Error	t-Value*	Pr >| t |**
Intercept	4.9237	1.2701	3.88	0.0001	4.8742	1.2760	3.82	0.0001
MALMQTFP	1.8454	0.4853	3.80	0.0002	1.8918	0.4908	3.85	0.0001
R^2	0.0182				0.0194			
F Test***								
Hausman Test****			0.67	0.4134				
F Test*****			14.46	0.0002			14.86	0.0001

Explanatory Variable	Econometric Model							
	Fixed Two				First-Order Autoregressive (Parks)			
	Estimate	Standard Error	t-Value*	Pr >| t |**	Estimate	Standard Error	t-Value*	Pr >| t |**
Intercept					3.1256	0.9196	3.40	0.0007
MALMQTFP	1.9166	0.4930	3.89	0.0001	4.0132	0.8655	4.64	<0.0001
R^2	0.7246				0.3879			
F Test***			5.12	<0.0001				
Hausman Test****								
F Test*****			15.11	0.0001			21.50	0.0001

* F value for F test for no fixed effects and F test of linear hypotheses about the regression parameters, m value for Hausman test for random effects.
** Pr > | F | for F test for no fixed effects and F test of linear hypotheses about the regression parameters, Pr > | m | value for Hausman test for random effects.
*** Test for no fixed effects.
**** Test for Random effects.
***** Test of linear hypotheses about the regression parameters.

the Da Silva (1975) method, and the first-order autoregressive model with heteroscedasticity and contemporaneous correlation between cross sections was estimated using the Parks (1967) method. The best Da Silva mixed variance-component moving average error model defined a three-year time period for the moving average.

Information in the tables includes parameter estimates, their standard errors, t-statistics and P-value, and the results of the specification tests. The first model (relationship between ROA and TE and SE) was tested for multicollinearity between the SE and TE variables using the Belsley et al. (1980) approach. The results showed no significant collinearity.

From Tables 4.13 and 4.14, it follows that the two-way random effects and the mixed variance-component moving average error models have almost identical parameter estimates as well as similar results of the tests of linear hypotheses about the regression parameters.

Results of Table 4.13 indicate that both TE and SE have positive effects on ROA. The TE effect was significant at the 1% level in all of the models but the first-order autoregressive, where it was significant at the 5% level. The SE effect was found to be significant at the 5% level in the random two-way effect and mixed variance-component moving average error models and at the 1% level in the first-order autoregressive model. The SE effect was not significant in the two-way fixed effects model. From Table 4.14, it follows that the Malmquist TFP indexes had positive and statistically significant (1% level) effects on ROA in all econometric model estimations.

The regressions results supported the initial hypothesis that all three independent variables had positive influences on ROA. Thus, it can be concluded that increases in efficiency and productivity improves farm financial performance, as represented by ROA.

Since panel data are used in the analysis, it would be appropriate to include a lagged dependent variable (ROA) on the right-hand side of the regression equations in both models for examining dynamic effects. However, the inclusion of the lagged dependent variable raises substantial complications in estimation of the models. The problem is that the lagged dependent variable is correlated with the disturbance in both the fixed and random effects settings (Greene, 1997).

The general approach to resolve this problem relies on instrumental variable estimators. After constructing instrumental variables for the lagged ROA variable, the time series were reduced to four years. Results of the econometric models (the first one estimating the relationship between ROA and technical and scale efficiencies, and the second one estimating the relationship between ROA and the Malmquist TFP indexes) using two-stage least squares estimation indicated positive relationships between ROA and all independent variables including lagged ROA.

The relationship between ROA and lagged ROA was significant at the 10% level in both models, indicating that farms with higher financial performance in the past tend to perform better in the present as well. The relationship between ROA and the Malmquist TFP indexes was significant at the 1% level; the relationship between ROA and TE was significant at the 5% level, while the SE variable was not significant.

However, the instrumental variables estimator neglects a lot of information and is, therefore, inefficient (Ahn and Schmidt, 1995). Also, after constructing instrumental variables for lagged ROA, the time series were reduced to four years. Neglecting information and a reduction of time series to four years did not allow establishing strong relationship between ROA and lagged ROA and the efficiency and productivity variables. As a result, the adjusted R^2 for the first model was only 0.010 and for the second model was 0.035.

Summary

Technical and scale efficiencies and Malmquist TFP indexes were calculated for a set of North Dakota farms. The panel data set consists of seven years of observations for 130 farms. The results demonstrate that, on average, farms were 0.75 technically efficient under the assumption of CRS, 0.79 technically efficient under the assumption of VRS, and 0.96 scale efficient. For this group of farms, outputs can potentially be increased by 25% while using the same amounts of inputs if all of the farms in the sample were operating on the efficiency frontier assuming CRS. Furthermore, no significant improvements in efficiency could be realized by the average farms in the sample by change in scale.

Over the 1995 to 2001 time period, there has been a modest productivity growth of approximately 1.7% per year. Most of the increase was attributed to technical change, while changes in technical efficiency had very small effects on the Malmquist TFP. Different trends in TFP and its components were found for each region in the data set.

It was found that farm technical efficiency is influenced by group and time effects. There is also a strong link between farm type and technical efficiency. However, it is unclear why such results are obtained. Furthermore, technical efficiency is positively influenced by farm size as measured in terms of accrual gross income and also positively influenced by the long-term debt-to-asset ratio. Part-time farmers are found to be less efficient in allocating their farm resources as compared to full-time farmers. Insurance payments and current debt-to-asset ratios negatively affect technical efficiency, while no statistically significant relationship was found between technical efficiency and the following variables: intermediate debt-to-asset ratio, farming experience, and government payments.

Strong and positive relationships between ROA and technical and scale efficiencies, and ROA and Malmquist TFP indexes, were found. These findings indicate that farm financial performance is largely dependent upon a producer's ability to stay on the production frontier and adopt new technologies.

CHAPTER V. SUMMARY AND CONCLUSIONS

Introduction

Chapter V provides an overview of the thesis, a summary of the procedures used, and conclusions drawn from the results. Limitations of the study are discussed, and directions for future research are proposed.

Thesis Summary

Linear programming models were employed to estimate technical and scale efficiency and productivity growth of selected North Dakota farms from all four geographic regions of the state on a yearly basis over seven years. Panel data of 910 records from 130 farms from 1995 to 2001 were used in the study. To estimate efficiency and productivity, the data for each farm in the sample were aggregated into seven categories: five inputs and two outputs. Categories of outputs included crop and livestock, and categories of the inputs included labor, operating expenses, crop acres, pasture acres, and capital.

Farm-level technical efficiency scores were used in a regression model to reveal the relationship between the efficiency measures and different farm-specific characteristics. Variables hypothesized to influence technical efficiency included farm location (group variable), year (time variable), farm type (crop, livestock, or mixed), leverage (short-term, intermediate-term, and long-term debt-to-asset ratios), non-farm income to total farm income ratio, experience (measured as number of years in the farm business), and insurance and government payments made to the farm.

Furthermore, two additional models were estimated to analyze how returns on assets (ROA) of individual farms are related to technical and scale efficiency and to determine if changes in farm productivity have an impact on a farm's financial performance.

Results and Conclusions

Findings of the research showed that, on average, farms under the analysis were 0.75 technically efficient under the assumption of constant returns-to-scale (CRS), 0.79 technically efficient under the assumption of variable returns-to-scale (VRS), and 0.96 scale efficient. Therefore, for these farms, outputs could potentially be increased by 25% while using the same amounts of inputs if all of the farms in the sample were operating on the efficiency frontier assuming CRS. No significant improvements in efficiency could be realized by the average farms in the sample by change in scale.

Tests for homogeneity of variance between efficiency ratios among the regions indicated that the equality of means for technical efficiency (TE) scores for all four regions under VRS is rejected at the 1% significance level for 1995 and 1999 and at the 10% significance level in all other years except for 1997. Equality of the means could not be rejected in any year for scale efficiency (SE), which indicates that average scale efficiency scores are statistically similar among all of the regions.

The results for each region indicated that Region 1 had better average TE scores than Region 2, better TE scores than Region 3 during all years but 1998 and 2000, and better mean TE scores than Region 4 in 1996 and 1999. Inability to reject the hypothesis of difference in mean TE scores between Regions 1 and 4 in 1995, 1998, and 2001 could be due to the fact that these regions did not have a sufficiently large number of farms in the analysis. Region 2 had the lowest average statistically significant TE scores as compared to all other regions in 1999 and 2000, while there was no statistically significant difference in TE scores between Regions 2 and 3 in all other years except for 1998.

Positive and statistically significant results of the Spearman Rank Correlation Coefficients (SRCC) test indicated that farms in the sample maintained their relative position to the production frontier as compared to other farms over both short (year to year) and long periods of time.

Over the 1995 to 2001 time period, there had been a modest productivity growth of approximately 1.7% per year. Most of the increase was attributed to technical change, while changes in technical efficiency had very small effects on the Malmquist TFP.

All regions experienced similar patterns in technical change. Another similarity among the regions was an absence of noticeable changes in farm location relative to the scale frontier. The absence of an apparent trend in efficiency change and, therefore, the Malmquist TFP index might be explained by the fact that farms in the sample produce different output mixes using different inputs as well as face dissimilar agro-climatic conditions.

Analysis of cumulative yearly changes in TFP and its components in each region indicates that in Region 1, changes in TFP were mostly attributed to technical change, while efficiency change had no significant impact on the TFP in any year except 2000. However, over the seven-year period, there have been no changes in either of the productivity factors in Region 1. The trend in all other regions was more striking. Each one of those regions experienced mean productivity growth of 1.2% to 2.7% per year as a result of mixed and often offsetting impacts of both technical and efficiency changes.

It was found that farm technical efficiency is influenced by group and time effects. There is a strong link between farm type and technical efficiency. However, it is unclear why such results are obtained.

Leverage variables DARC and DARL were statistically significant, while variable DARI was not significant. The results for DARI are consistent with the perfect market hypothesis and do not support the agency cost, free cash flow, or credit evaluation concepts of finance theory. Variable DARC has a negative influence on TE. The result contradicts the free cash flow concept and, at the same time, supports the agency cost concept in finance. Variable DARL has a positive influence on TE. This relationship is consistent with the credit evaluation concept, consequently indicating that bankers prefer to finance more efficient farmers, and is consistent with the concept that technical progress is embodied in long-term assets in agriculture.

Furthermore, technical efficiency is positively influenced by farm size as measured in terms of accrual gross income. Part-time farmers are found to be less efficient in allocating their farm resources as compared to full-time farmers. Insurance payments are negatively correlated with technical efficiency. There was no statistically significant relationship found between technical efficiency and the following variables: farming experience and government payments.

Strong and positive relationships between ROA and technical and scale efficiencies and ROA and Malmquist TFP indexes were found. These results indicate that farm financial performance is largely dependent upon a producer's ability to stay on the production frontier and adopt new technologies.

Limitations and Future Research

Study Limitations

The results of this study have to be interpreted with care due to several limitations attributed to the data set used and assumptions made while estimating technical and scale efficiency and productivity.

The first limitation of the research is that a criterion for farm selection was based on participation in the NDFRBM program for seven consecutive years. Therefore, the subset of farms in the analysis does not represent average North Dakota farms, and the results cannot be extrapolated to all agricultural producers in the state.

The second limitation is that the farms differ greatly in outputs produced. Out of 130 farms in the sample, 55 produced only crops while the remaining 75 had both crop and livestock enterprises. There were a total of 57 crop and 27 livestock enterprises, produced by at least one producer. Such a heterogeneity in outputs suggests the possibility of significant random noise among the observations since farms would use different technologies while producing such a large variation of crop and livestock products. The programming approach, which was used in the research, combines noise in the data set with inefficiency and identifies it all together as inefficiency. Thus, some farms may appear as inefficient although they were not.

The next limitation arises from farm specialization. Because of the output heterogeneity, it was not possible to construct output quantity indexes as should be done in order to estimate efficiency and productivity. Instead, both aggregated outputs, crops and livestock, were measured in terms of accrual revenues from all respective enterprises. Although output prices were adjusted by the annual average indexes of prices received, indexes for each of the crop and livestock products were not available. Outputs were aggregated into groups and prices in each group were adjusted by the same index. This aggregation introduced bias into the output measures, since prices of each individual product in the group did not change by the same percentage.

Directions for Future Research

Limitations of this study indicate implications for future research. First, incorporating more farms into the analysis would enable measurement of efficiency and productivity for subsets of homogeneous farms (e.g., to construct separate production frontiers for similar farms or for farms within the same geographical location), as well as for the whole data set. Comparison of results from both models for each farm could perhaps isolate the effects of random noise from differences in specialization or agro-climatic factors and their impacts on efficiency and productivity.

Second, examination of allocative efficiency using input and output prices might reveal additional differences among farms in terms of producers' ability to utilize cost-minimizing input ratios. It would also enable farm economic efficiency estimation and more rigorous analysis of the relationship between farm-specific factors and efficiency as well as the relationship between farm financial measures and efficiency. Additional examination of scope efficiency would reveal possible gains in economic efficiency due to the specialization or diversification in farm production.

A third direction would be an analysis of the effects of different government programs on farm efficiency for farms over time. Contrary to the initial hypothesis, results of this study indicated that mixed farms were more technically efficient than crop farms, and livestock farms were the most efficient. However, the basis for these results is unclear.

Another direction to consider would be the examination of the effects of risk decisions on farm profitability and efficiency, e.g., is there a relationship between variability in farm profits from one year to another and farm efficiency scores? For example, some farms obtain insurance coverage for additional risks, such as preventive planting, pest outbreak, or hail damage; use seed varieties that are resistant to certain crop diseases; use additional chemicals to preclude crop loss due to possible fungal outbreak; or hedge against market risks. These producers may appear as inefficient during the normal years because they use more resources as compared to the farmers who did not hedge against additional risks. However, use of additional resources, which reduce risk, ensures the consistency of their profits regardless of the outcome.

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APPENDIX A

*Code for Estimating Farm Technical and Scale Efficiencies, and Malmquist TFP Indexes and Their *Components; Written in GAMS.

```
OPTION DECIMALS=5;
OPTION LIMCOL=0;
OPTION LIMROW=0;
OPTION ITERLIM = 50000;
SETS   ID               farms ID number /1*130/
       YEAR                             /1995*2001/
       INPUTS           model inputs    /LABOR,OPEREXPS,TOTCROP,PASTURE,CAPITAL/
       OUTPUTS          model outputs   /CROPS,LVSK/
       INPLVSK          livestock enterprises which constitute lvsk output
                                        /2020    Beef, Bulls
                                        2040     Beef Cow-Calf
                                        2060     Beef Replacement Heifers
                                        2080     Beef, Custom Fed
                                        2100     Beef, Background Beef
                                        2140     Beef, Background_Heifers
                                        2180     Beef, Finish Beef Calves
                                        2260     Beef, Finish_Yrlg Steers
                                        2280     Beef, Grazing Beef
                                        2300     Beef, Grazing_Heifers
                                        2360     Broilers
                                        2420     Dairy
                                        2440     Dairy Heifers
                                        2460     Dairy Replacement Heifers
                                        2480     Dairy Steers
                                        2600     Hogs, Farrow To Finish
                                        2620     Hogs, Feeder_Pig Prod
                                        2640     Hogs, Finish_Feeder Pigs
                                        2680     Horses, Boarding
                                        2800     Sheep, Feeder_Lamb Prod
                                        2820     Sheep, Lamb_Finishing
                                        2860     Sheep, Market_Lamb Prod
                                        3060     Hogs, Contract
                                        3100     Beef, Finish_Cull Cows
                                        3140     Bison, Cow-Calf
                                        3160     Bison, Finish_Calves
                                        3220     Hogs, Weaning to Finish
                                        3240     Hogs, Contractor/
       INPMEAT(INPLVSK)     lvsk enterprises that produce meat
                                        /2020, 2040, 2080, 2100, 2140, 2180, 2260, 2280, 2300, 2360,
                                        2440, 2480, 2600, 2620, 2640, 2680, 2800, 2820, 2860, 3060,
                                        3100, 3140, 3160, 3220, 3240/
       INPDAIRY(INPLVSK)                /2420/
       INPOTHLV(INPLVSK)    enterprises that do not belong to the other two categories above
                                        /2060, 2460/
       LVSKVAR              /PRLVSK     price of livestock products
                            QUANLVSK    quantity of the product produced
                            TRLVSK      accrual revenue from selling livestock products/
       INPCROPS         crop enterprises /C26    Barley
```

C27	Barley, Malting
C83	Buckwheat
C125	Corn
C128	Corn, Ear
C311	Oats
C417	Rye
C482	Wheat, Durum
C488	Wheat, Spring
C489	Wheat, Winter
C89	Canola
C134	Crumble
C150	Flax
C308	Mustard Seed
C419	Safflower
C432	Soybeans
C450	Sunflower
C451	Sunflower, Confectionary
C1	Aftermath Grazing
C2	Alfalfa Seed
C43	Beans, Garbanzo
C54	Beans, Navy
C57	Beans, Pea
C127	Corn Silage
C210	Hay, Alfalfa
C224	Hay, Clover
C229	Hay, Fescue Grass
C231	Hay, Grass
C232	Hay, Green Chop
C235	Hay, Mixed
C236	Hay, Mixed_Alfalfa and Grass
C238	Hay, Native Grass
C239	Hay, Oats
C245	Hay, Small Grain
C248	Hay, Sudan Grass
C249	Hay, Summer Annual Grass
C250	Hay, Sweet Clover
C256	Haylage Alfalfa
C257	Haylage Grass
C258	Haylage Mixed
C275	Lentils
C302	Millet
C310	Oatlege
C339	Pasture
C351	Peas
C357	Field Peas
C418	Rye Silage
C429	Sorghum Silage
C430	Sorghum Grain
C444	Straw
C447	Sudex
C499	Custom Work
C500	Rented Out
C570	Barley Silage
C801	Double Crop
C802	Waste Acres
C448	Sugar Beets

```
                                C136     CRP/
    INPFEEDCR(INPCROPS)         feed crops
                                /C2, C26, C570, C27, C125, C127, C128, C210, C224, C229,
                                C231, C232, C235, C236, C238, C239, C245, C248, C249,
                                C250, C256, C257, C258, C302, C310, C311, C351, C357,
                                C418, C429, C430, C444, C447/
    INPFOODGR(INPCROPS)         food grains
                                /C83, C417, C482, C488, C489/
    INPOIL(INPCROPS)            oil bearing crops
                                /C89, C134, C150, C308, C419, C432, C450, C451/
    INPOTHCR(INPCROPS)          dry edible beans and sugar beets
                                /C43, C54, C57, C275, C448/
    INPOTHER(INPCROPS)          crops not included in any of the categories above
                                /C1, C136, C339, C500, C499, C801, C802/
    CROPVAR      crop variables /ACRES
                                YLD      yield
                                VPU      value per unit/
    INDEXES        indexes of prices received and paid
                                /FEEDI          feed crops
                                FOODGRI         food grains
                                OILCRI          oil bearing crops
                                OTHCRI          other crops
                                LVMEATI         meat products
                                LVDAIRI         dairy products
                                PAIDI           index for prices paid/
    SCORES    efficiency scores /TESCRS         technical efficiency CRS
                                TESVRS          technical efficiency VRS
                                SCEFF           scale efficiency
                                Dt-xt+1         "distance function [S(t), x(t+1), y (t+1)]"
                                Dt+1-xt         "distance function [S(t+1), x(t), y (t)]"/
    CHANGE       TFP productivity and its components
                                /EFFCH          efficiency change
                                PEFFCH          pure efficiency change
                                SCCH            scale change
                                TECHCH          technical change
                                MALMQTFP        Malmquist TFP/;

ALIAS (ID,ID1);

TABLE INPDATA(ID,YEAR,INPUTS)
$ONDELIM
$INCLUDE a:\INPUTFILE.CSV
$OFFDELIM
DISPLAY INPDATA;

TABLE CROPDATA(ID,YEAR,INPCROPS,CROPVAR)
$ONDELIM
$INCLUDE a:\ INPCROPS.CSV
$OFFDELIM
DISPLAY CROPDATA;

TABLE LVSKDATA(ID,YEAR,INPLVSK,LVSKVAR)
$ONDELIM
$INCLUDE a:\ INPLVSK.CSV
$OFFDELIM
DISPLAY LVSKDATA;
```

```
*INDEXES OF PRICES RECEIVED AND PAID, ANNUAL AVERAGES, NORTH DAKOTA,
*1990-92 = 1.00
*OPERATING EXPENSES ARE ADJUSTED IN THE INPDATA TABLE DIRECTLY

TABLE INDEXDATA(YEAR, INDEXES)

          FEEDI  FOODGRI  OILCRI  OTHCRI  LVMEATI  LVDAIRI  PAIDI
    1995  1.17   1.47     1.05    0.92    0.76     0.98     1.15
    1996  1.45   1.67     1.24    1.02    0.68     1.14     1.15
    1997  1.11   1.36     1.20    0.98    0.85     1.03     1.19
    1998  0.95   1.12     1.15    0.97    0.81     1.19     1.13
    1999  0.88   0.97     0.87    0.88    0.85     1.09     1.11
    2000  0.85   0.93     0.79    0.88    1.01     0.94     1.16
    2001  0.86   0.94     0.80    0.95    1.00     1.18     1.20;

PARAMETER TR(ID,YEAR,OUTPUTS), OUTQDATA(ID,YEAR,OUTPUTS);

TR(ID,YEAR,'LVSK') =
        SUM(INPMEAT,LVSKDATA(ID,YEAR,INPMEAT,'TRLVSK')) /
        INDEXDATA(YEAR,'LVMEATI') +
        SUM(INPDAIRY,LVSKDATA(ID,YEAR,INPDAIRY,'TRLVSK')) /
        INDEXDATA(YEAR,'LVDAIRI') +
        SUM(INPOTHLV,LVSKDATA(ID,YEAR,INPOTHLV,'TRLVSK'));
OUTQDATA(ID,YEAR,'LVSK')= TR(ID,YEAR,'LVSK');

TR(ID,YEAR,'CROPS') =
        SUM(INPFEEDCR,CROPDATA(ID,YEAR,INPFEEDCR,'ACRES') *
        CROPDATA(ID,YEAR,INPFEEDCR,'YLD') * CROPDATA(ID,YEAR,INPFEEDCR,'VPU')) /
        INDEXDATA(YEAR,'FEEDI') +
        SUM(INPFOODGR,CROPDATA(ID,YEAR,INPFOODGR,'ACRES') *
        CROPDATA(ID,YEAR,INPFOODGR,'YLD') * CROPDATA(ID,YEAR,INPFOODGR,'VPU')) /
        INDEXDATA(YEAR,'FOODGRI') +
        SUM(INPOIL,CROPDATA(ID,YEAR,INPOIL,'ACRES') *
        CROPDATA(ID,YEAR,INPOIL,'YLD') * CROPDATA(ID,YEAR,INPOIL,'VPU'))/
        INDEXDATA(YEAR,'OILCRI') +
        SUM(INPOTHCR,CROPDATA(ID,YEAR,INPOTHCR,'ACRES') *
        CROPDATA(ID,YEAR,INPOTHCR,'YLD') * CROPDATA(ID,YEAR,INPOTHCR,'VPU')) /
        INDEXDATA(YEAR,'OTHCRI') +
        SUM(INPOTHER,CROPDATA(ID,YEAR,INPOTHER,'ACRES') *
        CROPDATA(ID,YEAR,INPOTHER,'YLD') *
        CROPDATA(ID,YEAR,INPOTHER,'VPU'));
OUTQDATA(ID,YEAR,'CROPS') = TR(ID,YEAR,'CROPS');

DISPLAY OUTQDATA;

FILE OUTQ /a: \OUTQ.XLS/;
PUT OUTQ;
PUT 'ID       YEAR       TRCROP       TRLVSK'/;
LOOP ((ID,YEAR),
PUT ID.TL,YEAR.TL, OUTQDATA(ID,YEAR,'CROPS'), OUTQDATA(ID,YEAR,'LVSK')/);

VARIABLES Z;
POSITIVE VARIABLES THETA, THETAPT, THETAPT1, LAMBDA;
EQUATIONS       OBJTE, EQ1, EQ2, EQ3,
                OBJPT, EQ1PT, EQ2PT, EQ3PT,
```

```
                        OBJPT1, EQ1PT1, EQ2PT1, EQ3PT1;
*===========================================================================

OBJTE..                       Z =E= SUM((ID,YEAR),THETA(ID,YEAR));
EQ1(ID,YEAR,OUTPUTS)..  SUM(ID1,LAMBDA(ID,YEAR,ID1)*
                              OUTQDATA(ID1,YEAR,OUTPUTS))=G=
                              THETA(ID,YEAR)*OUTQDATA(ID,YEAR,OUTPUTS);
EQ2(ID,YEAR,INPUTS)..     SUM(ID1,LAMBDA(ID,YEAR,ID1)*
                              INPDATA(ID1,YEAR,INPUTS))
                               =L= INPDATA(ID,YEAR,INPUTS);
EQ3(ID,YEAR)..                SUM(ID1,LAMBDA(ID,YEAR,ID1)) =E= 1;
*===========================================================================

OBJPT..                        Z =E= SUM((ID,YEAR)$(ORD(YEAR) LT
                               CARD(YEAR)),THETAPT(ID,YEAR));
EQ1PT(ID,YEAR,OUTPUTS)$(ORD(YEAR) LT CARD(YEAR))..
                               SUM(ID1,LAMBDA(ID,YEAR,ID1)*
                               OUTQDATA(ID1,YEAR,OUTPUTS)) =G=
                               THETAPT(ID,YEAR)*
                               OUTQDATA(ID,YEAR+1,OUTPUTS);
EQ2PT(ID,YEAR,INPUTS)$(ORD(YEAR) LT CARD(YEAR))..
                                SUM(ID1,LAMBDA(ID,YEAR,ID1)*
                                INPDATA(ID1,YEAR,INPUTS))
                                =L= INPDATA(ID,YEAR+1,INPUTS);
EQ3PT(ID,YEAR)$(ORD(YEAR) LT CARD(YEAR))..
                                SUM(ID1,LAMBDA(ID,YEAR,ID1)) =E= 1;
*===========================================================================

OBJPT1..                        Z =E= SUM((ID,YEAR)$(ORD(YEAR) LT
                                CARD(YEAR)),THETAPT1(ID,YEAR));
EQ1PT1(ID,YEAR,OUTPUTS)$(ORD(YEAR) LT CARD(YEAR))..
                                SUM(ID1,LAMBDA(ID,YEAR,ID1)*
                                OUTQDATA(ID1,YEAR+1,OUTPUTS)) =G=
                           THETAPT1(ID,YEAR)*OUTQDATA(ID,YEAR,OUTPUTS);
EQ2PT1(ID,YEAR,INPUTS)$(ORD(YEAR) LT CARD(YEAR)).. SUM(ID1,LAMBDA(ID,YEAR,ID1)*
          INPDATA(ID1,YEAR+1,INPUTS)) =L= INPDATA(ID,YEAR,INPUTS);
EQ3PT1(ID,YEAR)$(ORD(YEAR) LT CARD(YEAR))..      SUM(ID1,LAMBDA(ID,YEAR,ID1)) =E= 1;
*===========================================================================

MODEL TECRS     /OBJTE,EQ1,EQ2/;
MODEL TEVRS     /OBJTE,EQ1,EQ2,EQ3/;
MODEL TECHPT    /OBJPT,EQ1PT,EQ2PT/;
MODEL TECHPT1   /OBJPT1,EQ1PT1,EQ2PT1/;

PARAMETER RESULT(ID,YEAR,SCORES);
TECRS.workspace =    40.00;
SOLVE TECRS USING LP MAXIMIZING Z;
DISPLAY THETA.L;
RESULT(ID,YEAR,'TESCRS') = 1/THETA.L(ID,YEAR);

TEVRS.workspace =    40.00;
SOLVE TEVRS USING LP MAXIMIZING Z;
DISPLAY THETA.L;
RESULT(ID,YEAR,'TESVRS') = 1/THETA.L(ID,YEAR);

RESULT(ID,YEAR,'SCEFF') = RESULT(ID,YEAR,'TESCRS')/RESULT(ID,YEAR,'TESVRS');
```

```
TECHPT.workspace =    40.00;
SOLVE TECHPT USING LP MAXIMIZING Z;
DISPLAY THETAPT.L;
RESULT(ID,YEAR,'Dt-xt+1')$(ORD(YEAR) LT CARD(YEAR)) = 1/THETAPT.L(ID,YEAR);

TECHPT1.workspace =    40.00;
SOLVE TECHPT1 USING LP MAXIMIZING Z;
DISPLAY THETAPT1.L;
RESULT(ID,YEAR,'Dt+1-xt')$(ORD(YEAR) LT CARD(YEAR)) = 1/THETAPT1.L(ID,YEAR);

DISPLAY RESULT;

FILE EFSCORES /a:\EFFSCORES.XLS/;
PUT EFSCORES;
PUT 'ID       YEAR       TESCRS       TESVRS       SCEFF       Dt-xt+1       Dt+1-xt'/;
LOOP((ID,YEAR),
PUT ID.TL,YEAR.TL,RESULT(ID,YEAR,'TESCRS'),RESULT(ID,YEAR,'TESVRS'),
RESULT(ID,YEAR,'SCEFF'),RESULT(ID,YEAR,'Dt-xt+1'),RESULT(ID,YEAR,'Dt+1-xt')/);

PARAMETER CHRESULT(ID,YEAR,CHANGE);

CHRESULT(ID,YEAR,'EFFCH')$(ORD(YEAR) LT CARD(YEAR)) =   RESULT(ID,YEAR+1,'TESCRS')
                              /RESULT(ID,YEAR,'TESCRS');

CHRESULT(ID,YEAR,'PEFFCH')$(ORD(YEAR) LT CARD(YEAR)) =  RESULT(ID,YEAR+1,'TESVRS')
                              /RESULT(ID,YEAR,'TESVRS');

CHRESULT(ID,YEAR,'SCCH')$(ORD(YEAR) LT CARD(YEAR)) =    CHRESULT(ID,YEAR,'EFFCH')
                              /CHRESULT(ID,YEAR,'PEFFCH');

CHRESULT(ID,YEAR,'TECHCH')$(ORD(YEAR) LT CARD(YEAR)) =
                              SQRT((RESULT(ID,YEAR,'Dt-xt+1')/RESULT(ID,YEAR+1,'TESCRS'))*
                              (RESULT(ID,YEAR,'TESCRS')/RESULT(ID,YEAR,'Dt+1-xt')));

CHRESULT(ID,YEAR,'MALMQTFP')$(ORD(YEAR) LT CARD(YEAR)) =
                              CHRESULT(ID,YEAR,'PEFFCH')
                              *CHRESULT(ID,YEAR,'SCCH')*CHRESULT(ID,YEAR,'TECHCH');

DISPLAY CHRESULT;

FILE PRDTY /a:\PRDTY.XLS/;
PUT PRDTY;
PUT 'ID       YEAR       EFFCH       PEFFCH       SCCH       TECHCH       MALMQTFP'/;
LOOP((ID,YEAR),
PUT ID.TL,YEAR.TL,CHRESULT(ID,YEAR,'EFFCH'),CHRESULT(ID,YEAR,'PEFFCH'),
                              CHRESULT(ID,YEAR,'SCCH'),CHRESULT(ID,YEAR,'TECHCH'),
                              CHRESULT(ID,YEAR,'MALMQTFP')/);
```

APPENDIX B

*Code for Estimating Tobit and OLS Models to Analyze the Relationship between Technical Efficiency and Farm-Specific Factors, and the Relationship between ROA and Efficiency, and ROA and Productivity; Written in SAS.

```
data analysis;
infile 'A:\regdata.txt' dlm='09'x dsd firstobs = 2;
input ID YEAR TESCRS SCEFF MALMQTFP ROE ROA DARC DARI DARL DAR
NFTIR FTYPE REGION AGE SQAGE INSUR GOVT INCACRGR TENURE YRSFARM
TOTACRES;

*proc print;
*proc corr data=analysis;

proc sort;
by id year;

data roa;
set analysis;
proc print;
var ID YEAR ROA TESCRS SCEFF MALMQTFP;

*EFFICIENCY;

*Model TSCSREG: ROA it = f (TESCRS it, SCEFF it);
PROC TSCSREG data = roa;
ID id year;
ROAEFF_TSCREG: MODEL roa = tescrs sceff / fixtwo noint;
test tescrs=0, sceff=0;

*Model TSCSREG: ROA it = f (TESCRS it, SCEFF it);
PROC TSCSREG data = roa;
ID id year;
ROAEFF_TSCREG: MODEL roa = tescrs sceff / ranone rantwo parks dasilva m = 3;
test tescrs = 0, sceff = 0;

*PRODUCTIVITY;

*Model TSCSREG: ROA it = f (MALMQTFP it);
PROC TSCSREG data = roa;
ID id year;
ROAMALMQ_TSCSREG: MODEL roa = / fixtwo noint;
test malmqtfp =0;

*Model TSCSREG: ROA it = f (MALMQTFP it);
PROC TSCSREG data = roa;
ID id year;
```

```
ROAMALMQ_TSCSREG: MODEL roa = malmqtfp / ranone rantwo parks dasilva m = 3;
test malmqtfp = 0;



*TOBIT LEFT CENSORED MODEL TE = f (REGION, YEAR, FTYPE, DARC, DARI, DARL,
NFTIR, YRSFARM, INSUR, GOVT, INCACRGR);
data te;
set analysis;
tescrs1 = 1-tescrs;
if tescrs1 <= 0 then lower = 0;
            else lower = tescrs1;

PROC LIFEREG data = te outset = OUTEST (keep = _scale_);
class region year ftype;
Tobit: model (lower, tescrs1) = region year ftype darc dari darl nftir yrsfarm insur govt
incacrgr / d = normal;
output out = OUT xbeta = Xbeta;
run;

Comparison of actual and predicted values;
data predict;
drop lambda _scale_ _prob_;
set out;
proc print;
if _n_ = 1 then set outest;
lambda = pdf ('NORMAL', Xbeta/_scale_)/cdf('NORMAL',Xbeta/_scale_);
predict = cdf('NORMAL',Xbeta/_scale_)*(Xbeta + _scale_*lambda);
label Xbeta = 'Mean of Unsensored Var'
    predict = 'Mean of Sensored Var';
run;
proc print data = predict noobs label;
var tescrs1 lower region year ftype darc dari darl nftir yrsfarm insur govt
incacrgr xbeta predict;
run;
```

APPENDIX C

Table C.1. Decomposition of Malmquist TFP Indexes: Farm Level

ID	YEAR	MALMQTFP	TECHCH	EFFCH	PEFFCH	SCCH
1	1996	0.75	0.99	0.76	0.75	1.01
2	1996	0.9	0.91	1	1.01	0.99
3	1996	0.91	0.9	1	0.95	1.05
4	1996	1.03	1.03	1	1	1
5	1996	0.97	1.01	0.96	0.96	1
6	1996	0.89	0.89	1	1	1
7	1996	0.74	0.9	0.83	0.83	1
8	1996	0.95	0.95	1	1	1
9	1996	0.94	0.94	1	1	1
10	1996	1.06	1.06	1	1	1
11	1996	0.71	0.94	0.75	0.75	1
12	1996	0.95	0.95	1	1	1
13	1996	1.22	1.22	1	1	1
14	1996	0.87	1.03	0.85	0.85	1
15	1996	0.92	0.94	0.98	1	0.98
16	1996	1.05	1.05	1	1	1
17	1996	0.84	0.93	0.9	0.9	1
18	1996	0.94	0.96	0.98	0.98	1
19	1996	1.57	0.93	1.69	1.68	1
20	1996	0.87	0.87	1	1	1
21	1996	1.16	0.94	1.23	1.23	1
22	1996	0.92	1.06	0.87	0.87	1
23	1996	0.82	0.99	0.83	0.87	0.96
24	1996	0.88	0.97	0.91	0.93	0.98
25	1996	1.27	0.93	1.36	1.39	0.98
26	1996	0.94	0.95	0.99	1	0.99
27	1996	0.88	0.96	0.92	0.91	1.01
28	1996	0.95	0.97	0.98	0.96	1.03
29	1996	0.91	0.91	1	1	1
30	1996	1.04	1.04	0.99	0.92	1.08
31	1996	0.55	1.01	0.54	0.52	1.05
32	1996	0.72	0.99	0.73	0.81	0.9
33	1996	1.26	1	1.26	1.27	1
34	1996	1.06	0.93	1.14	1.14	1
35	1996	0.88	0.98	0.89	0.9	1
36	1996	0.66	1	0.66	0.71	0.92
37	1996	1.02	0.97	1.05	1.19	0.88
38	1996	0.73	0.92	0.79	0.78	1.01
39	1996	0.97	1.07	0.91	0.96	0.95
40	1996	0.82	0.93	0.88	0.88	1
41	1996	1.36	1.11	1.22	1.23	0.99
42	1996	0.95	1.03	0.93	0.91	1.02
43	1996	1.02	1.02	1	1	1

Table C.1. (Continued)

44	1996	0.78	1.07	0.73	0.58	1.25
45	1996	0.72	0.92	0.79	0.8	0.98
46	1996	1.52	1.15	1.32	1.37	0.96
47	1996	0.92	1.1	0.83	0.89	0.94
48	1996	1.13	1.04	1.09	1.06	1.02
49	1996	0.88	0.93	0.94	1.05	0.9
50	1996	1.14	1.08	1.06	1.06	1
51	1996	0.79	0.96	0.82	0.85	0.97
52	1996	0.97	0.93	1.04	0.95	1.09
53	1996	0.52	0.93	0.56	0.56	1
54	1996	0.71	0.94	0.75	0.74	1.02
55	1996	1.13	1	1.13	1.14	0.99
56	1996	0.7	0.93	0.76	0.74	1.02
57	1996	1.07	0.96	1.11	1.09	1.02
58	1996	1.24	1.24	1	1	1
59	1996	0.89	0.94	0.95	0.96	0.99
60	1996	0.84	0.92	0.91	0.92	1
61	1996	0.72	1	0.72	0.72	1
62	1996	1.23	0.93	1.32	1	1.32
63	1996	1.19	1.19	1	1	1
64	1996	1.12	1.12	1	1	1
65	1996	0.51	0.91	0.55	0.61	0.92
66	1996	0.95	1.02	0.93	0.95	0.98
67	1996	0.98	0.92	1.07	1.1	0.98
68	1996	0.79	1.02	0.78	0.8	0.98
69	1996	0.71	0.9	0.78	0.78	1
70	1996	1.14	1.22	0.94	1	0.94
71	1996	0.9	0.99	0.91	0.91	1
72	1996	1.63	1.63	1	1	1
73	1996	0.75	1.06	0.7	0.7	1
74	1996	0.85	0.96	0.88	0.88	1
75	1996	0.85	1.11	0.76	0.78	0.98
76	1996	1.42	0.91	1.56	1.83	0.85
77	1996	0.91	1	0.91	1.05	0.86
78	1996	0.71	0.71	1	1	1
79	1996	1.25	1.14	1.1	1	1.1
80	1996	1.07	1.4	0.76	1	0.76
81	1996	0.98	1.06	0.92	0.95	0.97
82	1996	1.04	0.99	1.05	1	1.05
83	1996	1.03	1.04	0.99	1	1
84	1996	0.82	1.08	0.75	0.8	0.94
85	1996	0.87	1.15	0.76	0.74	1.03
86	1996	0.92	0.92	1	1	1
87	1996	2.24	0.98	2.29	2.38	0.96
88	1996	1.58	0.9	1.77	1.65	1.07
89	1996	0.9	1	0.9	1	0.9
90	1996	0.97	0.93	1.05	1.03	1.02
91	1996	1.08	1.03	1.06	1.09	0.97
92	1996	0.83	0.92	0.9	0.91	0.99

Table C.1. (Continued)

93	1996	1.25	1.04	1.2	1.27	0.95
94	1996	1	1.02	0.97	0.98	1
95	1996	0.94	1.06	0.89	0.88	1
96	1996	1.41	0.92	1.53	1.53	1
97	1996	1.22	0.96	1.27	1.28	0.99
98	1996	0.64	0.92	0.69	0.69	1
99	1996	1.41	1.04	1.36	1.32	1.03
100	1996	1.14	0.94	1.21	1.21	1
101	1996	0.84	1.11	0.76	0.84	0.91
102	1996	0.86	0.96	0.9	0.91	0.99
103	1996	1.49	0.95	1.57	1.59	0.99
104	1996	0.77	0.92	0.84	0.85	0.98
105	1996	0.95	1	0.95	0.94	1.02
106	1996	0.88	0.97	0.91	0.93	0.98
107	1996	0.98	1	0.98	0.91	1.08
108	1996	0.58	0.58	1	1	1
109	1996	0.93	0.98	0.95	0.96	0.99
110	1996	0.79	0.88	0.89	0.89	1
111	1996	0.67	1.09	0.61	0.6	1.03
112	1996	0.74	1.01	0.73	0.73	1
113	1996	0.84	0.84	1	1	1
114	1996	1.2	1.07	1.12	1.14	0.98
115	1996	0.85	0.85	1	1	1
116	1996	1.28	0.99	1.3	1.34	0.97
117	1996	1.02	1.02	1	1	1
118	1996	1.13	0.95	1.2	1.19	1
119	1996	1.21	1.06	1.14	1.17	0.98
120	1996	1.42	1.08	1.31	1.33	0.99
121	1996	0.85	1.03	0.83	0.89	0.94
122	1996	1.14	1.14	1	1	1
123	1996	0.93	1.06	0.88	1.06	0.83
124	1996	1.22	1.22	1	1	1
125	1996	1.01	0.95	1.07	1.05	1.01
126	1996	1.53	1.5	1.02	1.02	1.01
127	1996	0.71	0.9	0.79	0.76	1.05
128	1996	0.76	1.04	0.73	0.76	0.96
129	1996	0.88	0.92	0.96	0.92	1.04
130	1996	0.8	1.01	0.8	0.76	1.05
1	1997	0.89	0.95	0.94	0.93	1
2	1997	0.95	0.88	1.09	1.1	0.98
3	1997	0.81	0.92	0.88	0.9	0.98
4	1997	0.95	1.07	0.89	0.89	1
5	1997	0.85	1.01	0.84	0.84	1
6	1997	0.79	0.82	0.96	1	0.96
7	1997	1.29	0.93	1.38	1.41	0.98
8	1997	1	1	1	1	1
9	1997	0.97	0.97	1	1	1
10	1997	0.91	0.95	0.96	0.98	0.98
11	1997	1.3	1.03	1.26	1.26	1

Table C.1. (Continued)

12	1997	1.08	1.08	1	1	1
13	1997	0.74	0.76	0.97	1	0.97
14	1997	1	1.01	0.99	0.99	1
15	1997	0.9	0.96	0.94	1	0.94
16	1997	1.03	1.03	1	1	1
17	1997	1.08	1.07	1.01	1.01	1
18	1997	0.87	1.01	0.86	0.86	1
19	1997	0.85	0.92	0.92	0.92	1
20	1997	1	1	1	1	1
21	1997	0.84	0.92	0.91	0.92	1
22	1997	1.02	0.74	1.38	1.37	1
23	1997	1.16	0.94	1.23	1.25	0.98
24	1997	1.05	1.01	1.05	1.26	0.83
25	1997	0.95	0.92	1.04	1.06	0.98
26	1997	0.99	1	0.99	1	0.99
27	1997	0.96	0.88	1.09	1.03	1.06
28	1997	0.89	0.82	1.09	1.05	1.04
29	1997	0.8	0.88	0.9	0.91	0.99
30	1997	0.8	0.87	0.93	1.14	0.81
31	1997	0.98	0.95	1.03	1.06	0.97
32	1997	1.03	0.96	1.07	1.01	1.06
33	1997	0.93	0.74	1.26	1.29	0.97
34	1997	0.88	0.96	0.91	0.93	0.98
35	1997	0.79	0.94	0.84	0.82	1.02
36	1997	1.18	0.88	1.35	1.24	1.09
37	1997	1	0.87	1.16	1.01	1.15
38	1997	1.03	0.82	1.25	1.15	1.09
39	1997	1.55	0.96	1.63	1.41	1.16
40	1997	1.6	0.89	1.8	1.76	1.02
41	1997	0.93	0.9	1.03	1.03	1.01
42	1997	1.02	0.85	1.21	1.2	1
43	1997	1.21	1.21	1	1	1
44	1997	1.45	0.89	1.63	1.6	1.02
45	1997	1.07	0.84	1.28	1.24	1.03
46	1997	0.95	1.07	0.89	0.91	0.97
47	1997	1.2	1	1.19	1.09	1.09
48	1997	1.09	0.85	1.28	1.21	1.05
49	1997	1.33	0.92	1.45	1.28	1.13
50	1997	1.42	1.08	1.32	1.34	0.98
51	1997	1.02	0.87	1.17	1.09	1.08
52	1997	1.12	0.89	1.27	1.15	1.1
53	1997	1.61	0.95	1.69	1.64	1.03
54	1997	0.95	0.92	1.03	1.02	1.02
55	1997	1.21	0.86	1.4	1.36	1.03
56	1997	0.82	0.91	0.9	0.91	0.98
57	1997	1.08	0.86	1.26	1.29	0.98
58	1997	0.97	0.97	1	1	1
59	1997	0.97	0.93	1.05	1.04	1.01
60	1997	0.85	0.85	1.01	1.02	0.99

Table C.1. (Continued)

61	1997	1.43	0.94	1.53	1.6	0.95
62	1997	0.52	0.82	0.63	1	0.63
63	1997	0.82	0.97	0.84	1	0.84
64	1997	1.17	1.17	1	1	1
65	1997	1.46	0.89	1.63	1.52	1.07
66	1997	0.83	0.9	0.92	0.9	1.02
67	1997	0.61	0.94	0.65	0.64	1.01
68	1997	1	0.94	1.06	1.05	1.02
69	1997	1.21	0.89	1.36	1.37	0.99
70	1997	0.9	0.73	1.23	1	1.23
71	1997	0.95	0.93	1.03	1.03	0.99
72	1997	0.46	0.49	0.93	1	0.93
73	1997	1.23	0.86	1.43	1.43	1
74	1997	0.87	0.95	0.92	0.92	1
75	1997	1.05	0.87	1.21	1.19	1.02
76	1997	0.46	0.89	0.52	1.76	0.29
77	1997	0.85	0.9	0.95	0.81	1.17
78	1997	0.61	0.61	1	1	1
79	1997	0.73	0.73	1	1	1
80	1997	0.69	0.52	1.31	1	1.31
81	1997	1.18	0.88	1.34	1.27	1.05
82	1997	0.96	1.01	0.95	0.97	0.98
83	1997	0.99	0.94	1.05	1.04	1.01
84	1997	1.45	0.93	1.56	1.52	1.03
85	1997	1.02	0.86	1.19	1.21	0.98
86	1997	1.12	1.24	0.9	0.92	0.98
87	1997	1.18	0.88	1.34	1.52	0.88
88	1997	0.83	0.96	0.86	0.87	0.99
89	1997	0.68	0.92	0.73	0.95	0.77
90	1997	0.87	0.93	0.93	0.93	1
91	1997	0.92	0.87	1.05	1.03	1.02
92	1997	1.4	0.95	1.48	1.5	0.99
93	1997	1.14	0.9	1.26	1.19	1.06
94	1997	1.59	0.9	1.78	1.54	1.16
95	1997	1.04	0.9	1.15	1.14	1
96	1997	0.97	0.85	1.14	1.23	0.92
97	1997	0.78	0.9	0.87	0.87	1.01
98	1997	0.98	0.9	1.09	1.08	1.01
99	1997	1.26	0.88	1.43	1.35	1.06
100	1997	0.73	0.92	0.79	0.81	0.98
101	1997	1.32	0.89	1.48	1.39	1.06
102	1997	0.77	0.87	0.9	0.87	1.03
103	1997	0.91	0.86	1.06	1.04	1.02
104	1997	1.3	0.82	1.58	1.9	0.83
105	1997	1.09	0.95	1.16	1.11	1.04
106	1997	1	0.91	1.1	1.11	0.99
107	1997	0.97	0.88	1.11	1.3	0.85
108	1997	0.8	0.8	1	1	1

Table C.1. (Continued)

109	1997	1.5	1.07	1.41	1.39	1.01
110	1997	1.17	0.91	1.29	1.29	1
111	1997	1.71	0.98	1.75	1.75	1
112	1997	1.21	0.91	1.33	1.33	1
113	1997	1.39	1.39	1	1	1
114	1997	1.15	1.09	1.06	1.04	1.02
115	1997	1	1	1	1	1
116	1997	1.1	0.8	1.37	1.27	1.08
117	1997	0.82	0.93	0.88	0.91	0.97
118	1997	1	0.99	1.02	1	1.02
119	1997	0.6	1.08	0.55	0.54	1.02
120	1997	1.11	0.93	1.19	1.17	1.02
121	1997	1.08	1	1.08	1.04	1.04
122	1997	0.83	0.86	0.96	0.96	1
123	1997	1.21	0.93	1.3	1	1.3
124	1997	1	1	1	1	1
125	1997	1.04	1.04	1	1	1
126	1997	1.11	0.62	1.8	1.6	1.13
127	1997	0.73	0.84	0.86	0.88	0.98
128	1997	2.4	1.4	1.71	1.62	1.06
129	1997	1.12	0.83	1.36	1.53	0.89
130	1997	0.97	1.01	0.96	1.02	0.94
1	1998	1.37	0.87	1.57	1.59	0.99
2	1998	0.65	0.96	0.68	0.63	1.08
3	1998	0.95	0.96	0.99	0.98	1.02
4	1998	0.72	0.78	0.93	0.94	0.99
5	1998	0.92	0.83	1.11	1.11	1
6	1998	1.08	1.03	1.04	1	1.04
7	1998	0.77	0.88	0.87	0.93	0.94
8	1998	0.66	0.86	0.77	0.8	0.96
9	1998	0.8	0.8	1	1	1
10	1998	0.83	0.83	1.01	1.02	0.98
11	1998	0.73	0.87	0.84	0.84	1
12	1998	0.77	0.77	1	1	1
13	1998	0.93	0.91	1.02	0.99	1.03
14	1998	0.88	0.82	1.07	1.08	0.99
15	1998	0.9	0.79	1.15	1	1.15
16	1998	0.78	0.78	1	1	1
17	1998	0.82	0.88	0.94	1.03	0.91
18	1998	1.13	0.86	1.32	1.39	0.94
19	1998	1.03	0.94	1.09	1.08	1
20	1998	0.9	0.9	1	1	1
21	1998	1.05	0.87	1.22	1.21	1.01
22	1998	0.67	0.8	0.84	0.84	1
23	1998	0.95	0.86	1.11	0.96	1.17
24	1998	0.98	0.86	1.13	0.97	1.16
25	1998	0.9	0.95	0.95	0.93	1.02
26	1998	0.96	0.9	1.07	1	1.07

Table C.1. (Continued)

27	1998	1.25	1	1.25	1.27	0.98
28	1998	1.16	1.05	1.11	1.16	0.95
29	1998	1.02	0.99	1.03	1.04	1
30	1998	1.31	0.98	1.34	0.92	1.45
31	1998	1.42	0.91	1.56	1.48	1.05
32	1998	1.5	0.98	1.53	1.46	1.05
33	1998	1.29	1.03	1.25	1.22	1.03
34	1998	1.31	0.88	1.49	1.44	1.03
35	1998	1.07	0.92	1.16	1.13	1.03
36	1998	0.76	0.93	0.82	0.81	1.01
37	1998	0.97	1.11	0.88	0.88	1
38	1998	0.9	1.02	0.88	0.91	0.98
39	1998	0.88	1.05	0.84	0.91	0.92
40	1998	0.92	0.92	1.01	1.04	0.97
41	1998	1.11	1.04	1.07	1.06	1
42	1998	1.04	0.99	1.05	1.04	1.01
43	1998	0.85	0.85	1	1	1
44	1998	1.38	1.17	1.19	1.07	1.1
45	1998	0.81	1.04	0.78	0.77	1.01
46	1998	1.11	0.94	1.18	1.1	1.07
47	1998	1.12	0.97	1.16	1.14	1.02
48	1998	1.13	0.97	1.17	1.11	1.05
49	1998	0.96	1.05	0.92	0.81	1.13
50	1998	0.94	0.92	1.01	1	1.01
51	1998	0.75	1.06	0.71	0.72	0.99
52	1998	1.1	1.03	1.06	1.12	0.95
53	1998	1.09	0.77	1.41	1.48	0.95
54	1998	0.99	0.98	1.01	1.02	1
55	1998	0.97	1.04	0.93	0.93	1
56	1998	1.55	0.95	1.63	1.72	0.95
57	1998	0.93	1.07	0.87	0.84	1.03
58	1998	0.86	0.86	1	1	1
59	1998	0.78	0.98	0.8	0.75	1.07
60	1998	1.2	1.02	1.18	1.16	1.01
61	1998	0.96	0.92	1.04	1.01	1.03
62	1998	1.12	1.02	1.1	1	1.1
63	1998	1.02	0.93	1.09	0.93	1.18
64	1998	0.97	0.97	1	1	1
65	1998	1.18	0.96	1.24	1.23	1.01
66	1998	1.53	0.97	1.58	1.57	1
67	1998	1.34	0.96	1.39	1.38	1.01
68	1998	1.01	1	1.01	1.02	0.99
69	1998	1.12	0.99	1.13	1.11	1.01
70	1998	1.45	1.16	1.26	1	1.26
71	1998	1.08	0.96	1.13	1.14	0.99
72	1998	0.98	1.04	0.94	0.88	1.06
73	1998	0.81	0.81	1	1	1
74	1998	0.93	0.79	1.18	1.19	0.99

Table C.1. (Continued)

75	1998	1.16	0.98	1.18	1.18	1
76	1998	1.71	0.93	1.83	0.46	3.95
77	1998	1.47	1.12	1.32	1.24	1.07
78	1998	1.03	1.03	1	1	1
79	1998	0.95	1.07	0.89	0.9	0.99
80	1998	0.96	0.96	1	1	1
81	1998	1.1	0.97	1.14	1.14	1
82	1998	1.09	0.81	1.35	1.03	1.32
83	1998	1.62	0.87	1.87	1.89	0.99
84	1998	1.07	0.99	1.08	1.03	1.05
85	1998	1.47	1	1.46	1.42	1.03
86	1998	0.95	0.86	1.11	1.09	1.02
87	1998	1.53	1.16	1.32	1	1.32
88	1998	1.17	0.91	1.28	1.27	1.01
89	1998	1.41	0.93	1.52	1.05	1.44
90	1998	1.06	0.86	1.23	1.31	0.94
91	1998	0.98	1.08	0.92	0.91	1
92	1998	1.1	0.92	1.2	1.16	1.03
93	1998	1.21	0.96	1.26	1.25	1
94	1998	1.36	1.13	1.2	1.15	1.04
95	1998	1.13	0.99	1.15	1.2	0.96
96	1998	0.97	0.99	0.98	0.92	1.07
97	1998	1.19	0.97	1.22	1.21	1.01
98	1998	2.07	0.99	2.09	2.07	1.01
99	1998	1.21	0.91	1.33	1.33	1
100	1998	1.4	0.91	1.54	1.57	0.98
101	1998	1.17	1.12	1.05	1	1.05
102	1998	0.89	0.95	0.94	0.93	1.01
103	1998	1.37	1.05	1.3	1.3	1
104	1998	0.99	1.01	0.97	0.78	1.26
105	1998	1.08	0.93	1.16	1.16	1
106	1998	0.82	1.08	0.76	0.75	1.01
107	1998	1.25	1.16	1.08	1.04	1.04
108	1998	0.95	0.95	1	1	1
109	1998	1.02	1.02	1	1	1
110	1998	0.65	0.97	0.67	0.65	1.04
111	1998	0.84	0.95	0.89	0.85	1.04
112	1998	1.07	1.04	1.03	1.03	1
113	1998	0.66	0.66	1	1	1
114	1998	0.97	0.97	1	1	1
115	1998	0.84	0.88	0.95	1	0.95
116	1998	0.86	1	0.86	0.87	0.98
117	1998	0.86	1.03	0.83	0.83	1.01
118	1998	1.1	1.1	1	1	1
119	1998	1.49	0.88	1.69	1.74	0.97
120	1998	0.73	1	0.73	0.73	1.01
121	1998	1.23	0.95	1.3	1.22	1.07
122	1998	0.91	0.93	0.97	0.98	0.99

Table C.1. (Continued)

123	1998	0.73	0.96	0.76	0.96	0.8
124	1998	0.93	0.93	1	1	1
125	1998	0.71	0.91	0.78	0.79	0.99
126	1998	0.72	1.08	0.67	0.66	1
127	1998	1.16	1.03	1.12	1.09	1.03
128	1998	0.43	0.65	0.67	0.67	1
129	1998	1.13	1	1.13	1.11	1.02
130	1998	0.95	0.91	1.04	1.29	0.81
1	1999	1.34	1.35	0.99	1	0.99
2	1999	1.88	1.34	1.41	1.6	0.88
3	1999	1.37	1.43	0.95	0.95	1.01
4	1999	1.29	1.31	0.98	0.98	1
5	1999	1.43	1.43	1	1.02	0.98
6	1999	1.38	1.38	1	1	1
7	1999	1.39	1.3	1.07	1.02	1.04
8	1999	1.37	1.33	1.03	0.99	1.04
9	1999	1.02	1.11	0.92	0.93	0.99
10	1999	1.31	1.32	0.99	1	0.99
11	1999	1.18	1.2	0.99	0.99	1
12	1999	1.18	1.19	0.99	1	0.99
13	1999	1.21	1.23	0.99	0.99	1
14	1999	1.43	1.45	0.99	0.99	1
15	1999	1.43	1.43	1	1	1
16	1999	1.27	1.27	1	1	1
17	1999	1.31	1.29	1.01	1.07	0.95
18	1999	1.56	1.49	1.05	1	1.05
19	1999	1.48	1.48	1	1	1
20	1999	1.14	1.17	0.97	0.98	1
21	1999	1.25	1.41	0.89	0.91	0.98
22	1999	1.37	1.22	1.13	1.14	0.99
23	1999	1.27	1.31	0.97	0.97	0.99
24	1999	1.25	1.17	1.07	1.11	0.96
25	1999	1.05	1.25	0.85	0.87	0.97
26	1999	1.25	1.13	1.1	1	1.1
27	1999	1.13	1.27	0.89	0.88	1.01
28	1999	1.13	1.29	0.88	0.85	1.03
29	1999	1.66	1.43	1.16	1.16	1
30	1999	0.49	1.28	0.38	0.38	1.01
31	1999	0.6	1.25	0.48	0.47	1.02
32	1999	0.97	1.29	0.75	0.78	0.97
33	1999	0.98	1.19	0.82	0.81	1.01
34	1999	0.94	1.26	0.75	0.77	0.97
35	1999	1.34	1.29	1.04	1.05	0.99
36	1999	1.34	1.19	1.13	1.23	0.92
37	1999	1.27	1.2	1.06	1.05	1.01
38	1999	0.54	1.36	0.4	0.4	0.98
39	1999	1.78	1.2	1.49	1.37	1.08
40	1999	0.44	1.33	0.33	0.33	1

Table C.1. (Continued)

41	1999	1.24	1.11	1.12	1.12	1
42	1999	0.85	1.19	0.72	0.72	1
43	1999	1.47	1.47	1	1	1
44	1999	0.89	1.02	0.88	0.88	1
45	1999	1.14	1.38	0.83	0.84	0.99
46	1999	1.21	1.21	1	1	1
47	1999	1.12	1.24	0.91	0.92	0.99
48	1999	0.84	1.22	0.69	0.71	0.98
49	1999	0.28	1.23	0.23	1.23	0.18
50	1999	1.03	1.13	0.91	0.97	0.93
51	1999	1.56	1.24	1.26	1.26	1
52	1999	0.69	1.1	0.62	0.61	1.02
53	1999	0.16	1.37	0.11	0.11	1.02
54	1999	0.18	1.42	0.13	0.13	0.98
55	1999	0.92	1.23	0.75	0.78	0.96
56	1999	0.55	1.34	0.41	0.38	1.07
57	1999	0.64	1.27	0.51	0.51	1
58	1999	1.64	1.64	1	1	1
59	1999	0.7	1.38	0.51	0.59	0.85
60	1999	0.71	1.42	0.5	0.52	0.97
61	1999	0.54	1.22	0.44	0.42	1.05
62	1999	0.16	1.46	0.11	1	0.11
63	1999	1.35	1.3	1.04	1.08	0.97
64	1999	1.55	1.55	1	1	1
65	1999	0.48	1.37	0.35	0.38	0.93
66	1999	0.87	1.35	0.64	0.66	0.98
67	1999	0.54	1.24	0.44	0.44	0.99
68	1999	1.09	1.32	0.83	0.82	1
69	1999	0.94	1.29	0.73	0.73	1
70	1999	0.82	0.82	1	1	1
71	1999	1.21	1.4	0.86	0.85	1.02
72	1999	0.92	1.02	0.9	0.89	1.01
73	1999	1.19	1.19	1	1	1
74	1999	1.46	1.4	1.04	1.03	1.01
75	1999	1.15	1.1	1.04	1.06	0.99
76	1999	0.78	1.22	0.64	0.63	1.01
77	1999	0.73	1.22	0.6	0.71	0.84
78	1999	0.93	0.93	1	1	1
79	1999	1.79	1.59	1.13	1.12	1.01
80	1999	0.74	1.04	0.71	0.75	0.95
81	1999	0.89	1.17	0.76	0.89	0.85
82	1999	1.32	1.44	0.92	1	0.92
83	1999	1.05	1.19	0.88	0.86	1.02
84	1999	1.01	1.2	0.84	0.88	0.96
85	1999	0.76	1.08	0.71	0.71	0.99
86	1999	0.86	0.99	0.87	0.95	0.91
87	1999	1.55	1.55	1	1	1
88	1999	1.33	1.27	1.05	1.05	1

Table C.1. (Continued)

89	1999	1	1.3	0.77	0.96	0.81
90	1999	1.36	1.36	1	0.99	1.01
91	1999	0.83	1.23	0.68	0.7	0.97
92	1999	1.05	1.2	0.87	0.88	0.99
93	1999	1.02	1.21	0.84	0.86	0.97
94	1999	1.28	1.28	1	1	1
95	1999	1.32	1.26	1.05	1.09	0.97
96	1999	0.53	1.31	0.4	0.4	1
97	1999	1.14	1.21	0.95	0.95	1
98	1999	1.08	1.37	0.79	0.8	0.99
99	1999	1.22	1.2	1.02	1.01	1.01
100	1999	0.92	1.28	0.71	0.71	1
101	1999	1.02	1.11	0.92	1	0.92
102	1999	1.35	1.3	1.04	1.05	1
103	1999	0.99	1.2	0.83	0.83	1
104	1999	1.22	1.3	0.94	1.2	0.78
105	1999	1.28	1.28	1	1	1
106	1999	1.68	1.23	1.37	1.38	1
107	1999	0.91	1.17	0.78	0.76	1.02
108	1999	0.89	0.89	1	1	1
109	1999	1.37	1.37	1	1	1
110	1999	0.88	1.39	0.64	0.63	1.01
111	1999	1.4	1.21	1.16	1.26	0.92
112	1999	1.06	1.15	0.92	0.92	1
113	1999	1.29	1.29	1	1	1
114	1999	1.33	1.33	1	1	1
115	1999	1.15	1.09	1.05	1	1.05
116	1999	1.14	1.24	0.92	0.96	0.95
117	1999	1.39	1.04	1.34	1.34	1
118	1999	1.03	1.03	1	1	1
119	1999	1.19	1.41	0.84	0.83	1.02
120	1999	1	1.18	0.85	0.86	0.99
121	1999	1.12	1.26	0.88	0.91	0.97
122	1999	1.06	1.17	0.91	0.91	0.99
123	1999	1.2	1.35	0.89	0.76	1.16
124	1999	1.25	1.25	1	1	1
125	1999	1.38	1.13	1.23	1.27	0.97
126	1999	0.89	1.32	0.67	0.69	0.96
127	1999	1.13	1.35	0.84	0.84	1
128	1999	1.46	1.29	1.13	1.17	0.97
129	1999	0.3	1.46	0.21	0.22	0.96
130	1999	1.21	1.36	0.89	0.88	1.01
1	2000	0.69	1.08	0.64	0.64	1
2	2000	0.88	0.97	0.91	0.87	1.04
3	2000	0.93	0.94	0.99	1.03	0.96
4	2000	1.02	1.06	0.96	0.95	1.01
5	2000	0.97	0.94	1.04	1.06	0.98
6	2000	0.79	0.98	0.81	0.96	0.84

Table C.1. (Continued)

7	2000	0.91	1.05	0.87	0.92	0.95
8	2000	1.06	0.94	1.12	1.13	0.99
9	2000	0.91	1.06	0.86	0.94	0.91
10	2000	0.7	0.99	0.71	0.72	1
11	2000	1.15	1.01	1.14	1.14	1
12	2000	0.8	1.04	0.77	0.78	0.98
13	2000	1.05	1.02	1.03	1.02	1
14	2000	1.07	1.01	1.06	1.17	0.9
15	2000	0.81	1.07	0.76	0.78	0.98
16	2000	1.25	1.25	1	1	1
17	2000	1.11	0.96	1.16	1	1.16
18	2000	0.78	0.96	0.81	0.82	0.99
19	2000	0.84	0.91	0.93	0.95	0.98
20	2000	1.06	1.03	1.03	1.02	1
21	2000	0.96	0.89	1.07	1.06	1.01
22	2000	0.89	1.11	0.8	0.82	0.97
23	2000	1.35	1.31	1.03	1.07	0.97
24	2000	0.91	1.1	0.83	0.89	0.93
25	2000	1.22	1.14	1.07	1.12	0.95
26	2000	0.96	1.03	0.93	1	0.93
27	2000	0.59	1.1	0.54	0.54	1
28	2000	0.64	0.92	0.7	0.69	1.02
29	2000	0.72	0.94	0.76	0.77	0.98
30	2000	0.96	1.15	0.83	0.85	0.98
31	2000	1.18	1.3	0.91	1.03	0.88
32	2000	1.07	0.97	1.11	1.08	1.03
33	2000	0.77	0.97	0.79	0.79	1
34	2000	1.06	1.12	0.95	0.93	1.02
35	2000	1.01	1.19	0.85	0.89	0.95
36	2000	0.85	1.06	0.8	0.8	1
37	2000	1.08	1.3	0.83	0.88	0.95
38	2000	2.38	1.16	2.05	1.96	1.05
39	2000	0.68	1.01	0.67	0.69	0.97
40	2000	2.35	1.13	2.07	2.04	1.02
41	2000	1.01	1.1	0.92	0.95	0.97
42	2000	1.4	1.09	1.29	1.32	0.97
43	2000	0.81	0.81	1	1	1
44	2000	0.78	1.11	0.7	0.79	0.89
45	2000	1.44	1.06	1.36	1.37	1
46	2000	0.79	0.79	1	1	1
47	2000	0.85	0.86	0.98	0.97	1.02
48	2000	1.1	1.01	1.09	1.06	1.02
49	2000	3.43	1.29	2.66	1	2.66
50	2000	0.7	0.87	0.8	0.8	1
51	2000	1.03	0.93	1.11	1.1	1
52	2000	1.63	1.14	1.43	1.49	0.96
53	2000	9.96	1.17	8.5	9.25	0.92
54	2000	11.35	10.82	1.05	0.97	11.08

Table C.1. (Continued)

55	2000	1.06	0.98	1.09	1.07	1.01
56	2000	2.58	1.08	2.39	2.42	0.99
57	2000	1.66	1.02	1.63	1.64	0.99
58	2000	0.68	0.68	1	1	1
59	2000	2.45	0.94	2.62	2.34	1.12
60	2000	2.65	1.1	2.42	2.33	1.04
61	2000	3.5	1.15	3.05	3.56	0.86
62	2000	11.3	10.8	1.04	0.97	11.08
63	2000	0.77	0.83	0.93	1	0.93
64	2000	0.45	0.45	1	1	1
65	2000	2.31	1.08	2.14	1.99	1.08
66	2000	1.2	0.9	1.34	1.42	0.94
67	2000	2.11	1.04	2.04	2.1	0.97
68	2000	1.34	0.95	1.41	1.46	0.97
69	2000	1.47	1.25	1.18	1.27	0.92
70	2000	0.85	0.98	0.87	1	0.87
71	2000	1.23	1.02	1.21	1.23	0.98
72	2000	1.15	1.06	1.08	1.17	0.92
73	2000	1.26	1.26	1	1	1
74	2000	1.21	1.21	1	1	1
75	2000	1.09	0.99	1.11	1.09	1.01
76	2000	2.2	1.21	1.82	2.04	0.89
77	2000	1.05	1.01	1.04	0.91	1.15
78	2000	1.62	1.62	1	1	1
79	2000	0.71	0.93	0.76	0.79	0.96
80	2000	1.35	1.18	1.14	1.2	0.94
81	2000	0.98	1.03	0.95	0.86	1.1
82	2000	1.01	1.09	0.93	0.88	1.06
83	2000	1.22	1.2	1.02	1.06	0.96
84	2000	1.1	0.98	1.12	1.1	1.02
85	2000	0.9	1.07	0.84	0.9	0.93
86	2000	1.11	0.96	1.15	1.05	1.1
87	2000	0.97	0.97	1	1	1
88	2000	0.75	1.33	0.56	0.65	0.87
89	2000	1.28	1.18	1.09	1.05	1.04
90	2000	0.96	1.29	0.74	0.8	0.93
91	2000	1.73	0.98	1.76	1.73	1.01
92	2000	1.63	1.42	1.15	1.14	1.01
93	2000	1	1.14	0.88	0.85	1.02
94	2000	1.12	1.22	0.92	0.99	0.93
95	2000	1.18	0.89	1.32	1.61	0.82
96	2000	1.89	1.2	1.57	1.75	0.9
97	2000	0.92	1.18	0.77	0.78	1
98	2000	0.99	1.04	0.95	0.95	1
99	2000	1.04	1.02	1.02	1.16	0.88
100	2000	1.3	1.14	1.14	1.19	0.96
101	2000	0.78	1.11	0.7	0.76	0.92
102	2000	0.96	0.99	0.97	0.99	0.98

Table C.1. (Continued)

103	2000	1.36	1.13	1.2	1.2	1
104	2000	1.3	1.21	1.07	1.08	0.99
105	2000	1.36	1.36	1	1	1
106	2000	0.81	0.96	0.84	0.84	1
107	2000	0.94	1.01	0.93	0.96	0.96
108	2000	1.01	1.01	1	1	1
109	2000	0.79	0.86	0.93	1	0.93
110	2000	2.28	0.99	2.3	2.34	0.98
111	2000	0.76	0.91	0.83	0.8	1.04
112	2000	1.12	1.02	1.09	1.09	1
113	2000	0.71	0.92	0.77	0.78	0.99
114	2000	0.93	0.93	1	1	1
115	2000	1.03	1.05	0.98	1	0.98
116	2000	1.08	1.15	0.93	0.89	1.05
117	2000	0.75	0.99	0.76	0.87	0.87
118	2000	1.04	1.04	1	1	1
119	2000	0.95	0.86	1.11	1.19	0.94
120	2000	1.68	1.05	1.6	1.6	1
121	2000	1.11	1.03	1.08	1.17	0.92
122	2000	1.02	0.95	1.07	1.08	1
123	2000	1.51	1.01	1.49	1.37	1.09
124	2000	0.9	0.9	1	1	1
125	2000	1.02	1.07	0.95	0.91	1.04
126	2000	1.42	0.98	1.45	1.44	1.01
127	2000	1.26	1.08	1.17	1.19	0.98
128	2000	1.12	0.99	1.13	1.13	1
129	2000	3.08	0.97	3.19	2.94	1.08
130	2000	0.78	0.88	0.89	1.13	0.78
1	2001	1.67	0.89	1.88	1.84	1.02
2	2001	0.9	1.01	0.89	0.79	1.13
3	2001	0.9	0.99	0.91	0.87	1.04
4	2001	1	1.01	1	1.03	0.97
5	2001	0.76	1.01	0.76	0.73	1.04
6	2001	0.96	0.96	1	0.91	1.1
7	2001	1.15	0.94	1.23	1.15	1.07
8	2001	0.95	0.99	0.96	0.95	1.01
9	2001	1.14	0.99	1.16	1.09	1.06
10	2001	1.2	1	1.2	1.17	1.02
11	2001	0.96	0.93	1.03	1.02	1
12	2001	0.99	1.01	0.98	0.99	0.99
13	2001	0.99	0.99	1	1	1
14	2001	0.94	0.99	0.95	0.87	1.09
15	2001	1.06	0.98	1.08	1.15	0.94
16	2001	0.95	0.95	1	1	1
17	2001	0.88	1.01	0.88	1	0.88
18	2001	1.09	1.03	1.05	1.05	1.01
19	2001	1.11	1.03	1.08	1.06	1.02
20	2001	0.86	0.92	0.93	0.93	1

Table C.1. (Continued)

21	2001	1.01	1.03	0.98	0.97	1.01
22	2001	1.2	0.96	1.25	1.23	1.02
23	2001	1.19	0.93	1.28	1.23	1.04
24	2001	1.16	0.96	1.21	1.13	1.08
25	2001	1.24	0.95	1.32	1.16	1.14
26	2001	1.18	1.04	1.14	1	1.14
27	2001	1.4	0.94	1.49	1.58	0.94
28	2001	1.79	1.03	1.74	1.74	1
29	2001	0.53	0.97	0.54	0.53	1.02
30	2001	1.36	0.84	1.61	1.65	0.98
31	2001	1.11	0.76	1.47	1.45	1.01
32	2001	1.36	1.01	1.34	1.33	1
33	2001	0.49	0.97	0.51	0.53	0.97
34	2001	0.83	0.86	0.97	0.96	1
35	2001	1.04	0.79	1.31	1.26	1.03
36	2001	0.94	0.85	1.11	1.16	0.95
37	2001	0.7	0.78	0.9	0.88	1.02
38	2001	1.38	0.9	1.54	1.59	0.96
39	2001	1.25	0.88	1.43	1.4	1.02
40	2001	1.11	0.81	1.37	1.34	1.02
41	2001	1.09	0.9	1.21	1.18	1.02
42	2001	0.77	0.86	0.9	0.88	1.03
43	2001	1.05	1.05	1	1	1
44	2001	0.86	0.89	0.96	0.87	1.11
45	2001	1.32	0.81	1.62	1.72	0.94
46	2001	1.03	1.03	1	1	1
47	2001	1.15	1.08	1.07	1.09	0.98
48	2001	0.93	0.95	0.97	1.03	0.95
49	2001	1.34	0.79	1.7	1	1.7
50	2001	1.41	1.04	1.36	1.32	1.04
51	2001	0.88	0.99	0.88	0.96	0.91
52	2001	0.81	0.78	1.03	1.04	0.99
53	2001	0.81	0.85	0.95	0.86	1.09
54	2001	0.96	0.91	1.05	1.08	0.97
55	2001	0.99	0.94	1.05	1.15	0.92
56	2001	0.96	0.81	1.19	1.21	0.98
57	2001	1.16	0.9	1.29	1.29	1
58	2001	0.98	0.98	1	1	1
59	2001	0.64	0.96	0.66	0.63	1.05
60	2001	0.76	0.82	0.93	0.99	0.93
61	2001	0.73	0.8	0.92	0.86	1.06
62	2001	0.78	0.96	0.81	1	0.81
63	2001	0.97	1.06	0.91	0.86	1.06
64	2001	0.6	0.95	0.63	0.65	0.96
65	2001	1.01	0.85	1.2	1.26	0.95
66	2001	0.98	0.91	1.08	0.99	1.09
67	2001	0.9	0.87	1.03	1	1.04
68	2001	0.82	0.94	0.87	0.85	1.02

Table C.1. (Continued)

69	2001	1.03	0.78	1.32	1.29	1.02
70	2001	0.82	0.86	0.95	1	0.95
71	2001	0.99	0.92	1.08	1.06	1.01
72	2001	1.08	0.92	1.18	1.09	1.09
73	2001	1.09	1.09	1	1	1
74	2001	0.93	0.98	0.95	0.99	0.96
75	2001	0.86	0.94	0.91	0.92	1
76	2001	0.7	0.83	0.85	0.83	1.02
77	2001	1.3	0.99	1.32	1.49	0.88
78	2001	0.89	0.89	1	1	1
79	2001	0.72	0.9	0.8	0.8	1
80	2001	0.92	0.89	1.03	0.97	1.07
81	2001	1.17	0.94	1.25	1.16	1.08
82	2001	1	0.95	1.05	1.06	0.99
83	2001	0.94	0.84	1.12	1.08	1.04
84	2001	0.89	0.91	0.97	1	0.97
85	2001	0.84	0.89	0.94	0.91	1.03
86	2001	0.89	0.95	0.94	0.95	0.99
87	2001	0.88	0.88	1	1	1
88	2001	1.04	0.74	1.4	1.26	1.11
89	2001	0.6	0.84	0.71	0.68	1.05
90	2001	0.71	0.79	0.9	0.81	1.11
91	2001	0.85	0.93	0.92	0.9	1.02
92	2001	0.69	0.73	0.94	1	0.94
93	2001	1.02	0.89	1.15	1.15	1
94	2001	0.85	0.99	0.87	0.89	0.97
95	2001	0.73	1.03	0.71	0.63	1.12
96	2001	1.03	0.77	1.34	1.23	1.09
97	2001	0.67	0.93	0.72	0.77	0.93
98	2001	0.9	0.94	0.96	0.97	0.98
99	2001	0.99	1.07	0.93	0.93	1
100	2001	0.86	0.83	1.04	1.03	1.01
101	2001	1.01	0.96	1.06	1.01	1.05
102	2001	1.19	1	1.19	1.19	1
103	2001	0.76	0.94	0.81	0.82	0.98
104	2001	0.94	0.83	1.14	1	1.14
105	2001	0.76	0.76	1	1	1
106	2001	0.91	0.94	0.97	0.95	1.02
107	2001	1.26	0.86	1.46	1.54	0.95
108	2001	0.75	0.82	0.92	1	0.92
109	2001	0.99	1.04	0.96	0.91	1.05
110	2001	0.93	0.93	0.99	1.01	0.98
111	2001	1.12	0.96	1.17	1.15	1.02
112	2001	0.8	0.94	0.85	0.92	0.93
113	2001	0.83	1.06	0.79	0.79	1
114	2001	0.92	0.92	1	1	1
115	2001	1.09	1.07	1.02	1	1.02
116	2001	1.08	0.84	1.29	1.35	0.95

Table C.1. (Continued)

117	2001	1.21	0.95	1.27	1.14	1.11
118	2001	0.93	0.93	1	1	1
119	2001	0.9	1.04	0.87	0.86	1.01
120	2001	0.85	0.83	1.02	1.02	1
121	2001	0.83	0.85	0.97	0.93	1.05
122	2001	1.09	0.98	1.11	1.09	1.02
123	2001	0.61	0.79	0.77	0.81	0.95
124	2001	0.94	0.94	1.00	1.00	1.00
125	2001	1.27	1.14	1.11	1.1	1.01
126	2001	1.11	0.93	1.19	1.16	1.02
127	2001	0.75	0.86	0.87	0.88	0.99
128	2001	1.09	0.93	1.17	1.13	1.03
129	2001	1.31	0.96	1.36	1.29	1.06
130	2001	1.14	0.98	1.17	1.00	1.17