EFFICIENCY AND PRODUCTIVITY MEASUREMENTS TO ANALYZE FARM-LEVEL IMPACTS FROM ADOPTION OF BIOTECHNOLOGY ENHANCED SOYBEANS

by

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B.S., University of Missouri, 1995
M.S., Texas A&M University, 1997

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

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Department of Agricultural Economics
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Abstract

This study focuses on the productivity and on-farm efficiency impacts of adopting biotechnology enhanced soybeans (BES). Previous research suggests the adoption of BES and subsequent time savings resulted in labor allocation to off-farm employment and reduced on-farm efficiency.

Using continuous panel data for 129 farms enrolled in the Kansas Farm Management Association (KFMA) with production and financial crop records from 1993 through 2011 that also provided information on their BES adoption experience, this study provides estimates on the technical efficiency, cost efficiency, and Malmquist productivity indexes (MI) with decompositions into efficiency change (EC) and technical change (TC) to provide insights on the impacts of adopting BES for set of sample farms.

Using data envelopment analysis to construct nonparametric efficiency frontiers and measurements assuming constant returns-to-scale (CRS) and variable returns-to-scale (VRS) technologies for the farms, this study provides insights on the impact of yield impacts of BES adoption. A biennial Malmquist productivity index (BMI) is developed to consider estimation of the productivity impacts between BES adopters and non-adopters assuming VRS. This analysis used five input categories: Labor, general, direct inputs, maintenance, and energy; and five outputs: corn, soybeans, sorghum, wheat, and other crops.

Tobit regression analysis of the panel of Kansas farms provided evidence of a positive impact from adoption of biotechnology enhanced soybeans on on-farm technical efficiency. Kolmogorov-Smirnov goodness-of-fit distributional hypothesis tests showed significant differences between analyzing the farms under CRS and VRS assumptions. T-tests showed a bias existed when assuming CRS if the true underlying technology was VRS in productivity

analysis. However, there was not a strong statistically significant difference between the distributions of productivity measures from the underlying populations of BES adopters and non-adopters in the sample of Kansas farms.

A revenue-indirect cost efficiency analysis of the sample farms demonstrated that different conclusions were reached under CRS and VRS when considering the differences in the average of the means of estimated efficiency scores and Tobit regression results considering BES adoption. Assuming CRS resulted in positive marginal effects for adopting BES of 0.017 significant at the 5% level. The marginal effect of BES adoption was not statistically significant under VRS.

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"We are like dwarfs sitting on the shoulders of giants. We see more, and things that are more distant, than they did, not because our sight is superior or because we are taller than they, but because they raise us up, and by their great stature add to ours."

- John of Salisbury, *Metalogico*, 1159 A.D.

"If I have seen a little further it is by standing on the shoulders of Giants."

-Isaac Newton, A personal letter to Robert Hooke, 1676 A.D.

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"I have a computer and the knowledge of the known world recorded in print and available electronically. With those resources I can do several things that would have taken lifetimes for mortal men to accomplish after the Tower of Babel was toppled. What the next generations will do should grow even further; unless we are toppled again for our audacity.
"Scientific work can gain much, and yet man gains nothing."

-Samuel Funk, 2012 A.D.

"Gravity explains the motions of the planets, but it cannot explain who set the planets in motion. God governs all things and knows all that is or can be done."

-Isaac Newton (attributed)

“Therefore being justified by faith, we have peace with God through our Lord Jesus Christ:

“By whom also we have access by faith into this grace wherein we stand, and rejoice in hope of the glory of God.

“And not only so, but we glory in tribulations also: knowing that tribulation worketh patience;

“And patience, experience; and experience, hope:

“And hope maketh not ashamed; because the love of God is shed abroad in our hearts by the Holy Ghost which is given unto us.”

Romans 5:1-5

Thankfully, these messages and the wisdom that matters in this world and the next were passed to me in the Bible. All I ever really needed to know I learned in Sunday School. Thankfully the messages became more real to me in a practical manner as I grew in knowledge and wisdom – even into the silver years. This degree required I surrender to Him and die daily to self. Not an easy thing – but sure better than trying to do it on my own. Not perfect, but a sinner saved by grace through faith in my Lord and Saviour Jesus Christ. All praise to the one true God who alone is worthy.

Thanks to the farmers and ranchers of Kansas and especially those who are members of the Kansas Farm Management Association. For your efforts building a world-class Research & Extension Program with summarized data to benefit all, may you find greater reward individually as your business intelligence is enhanced with tailored insights because your individual farm information is compared and reported directly.

Thanks to the men and women of the Kansas Farm Management Association team who provided the venue to make the survey tool a useful one in this scholarly study. I am grateful to

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I end with an acknowledgement of the lineage of which I am blessed to be part. May we honor those to whom honor is due; may we lift each other up; and may we look forward to the coming day with purpose.

Dedication

To my loving wife, Karisa and our wonderful children: Christopher, Katie, Rachel, Margaret, Timothy, Abigail, Elizabeth, John, and Amelia. May all praise be to the one true God.

Chapter 1 - Introduction

The United States Department of Agriculture (USDA) reports that 93% of the acres planted to soybeans in the United States for 2011 were planted to biotechnology enhanced soybeans (BES). The largest portion of these BES were of herbicide-tolerant (HT) varieties. HT varieties are designed to survive chemical herbicide treatments that would otherwise destroy or severely damage the yield potential of soybeans – making broad-spectrum herbicides an option for controlling targeted weeds after emergence of the crop (Fernandez-Cornejo and Caswell, 2006).

Early expectations by farmers of greater yields through BES have generally not been realized (Fernandez-Cornejo and Caswell, 2006). However, the broad and sustained adoption of BES indicates that some benefit has been realized by farmers. Fernandez-Cornejo and Caswell (2006) and Fernandez-Cornejo (2007) suggest that simplicity of weed control and less management time – with a suggestion that off-farm employment is increased – are factors that may contribute to the adoption of BES. The time savings may also have enabled a greater number of acres to be farmed.

1.1 Need for the Study

The prevalence of BES technologies makes understanding on-farm efficiency impacts of interest. No analyses of BES technology using a balanced panel of farms were found in the literature. There exist cross-sectional analyses (Goodwin and Mishra, 2004; Fernandez-Cornejo, Hendricks, and Mishra, 2005; and Fernandez-Cornejo, 2007) that focus on the impact off-farm employment has on-farm efficiency – but the focus was not on the impacts of BES. Fernandez-Cornejo and Caswell (2006) focused their attention on the first decade of genetically engineered crops, but did not explicitly examine efficiency of BES beyond citing there were no particular correlation with net farm returns and the use of time savings for off-farm employment.

This study builds on prior literature and advances the study of BES by considering a balanced panel dataset of Kansas farms for a 19-year period that starts three years prior to the commercial introduction of BES varieties. The extended period of time allows for possible technical regress from weather or other adoption impacts while providing an extended period of time to capture the potential for measurable technical progress over a longer time horizon that might have occurred with the broadly adopted BES technology.

The panel data set available in this study includes information on the first year of BES adoption for farms in the sample and allows for the study of: (1) the comparison of technical efficiency between adopters and non-adopters of BES across multiple years; (2) changes in productivity through differences in efficiency change and technical change between BES adopters and non-adopters using Malmquist indices; and (3) efficiency analysis of BES using a cost-minimization problem that is revenue-constrained to examine efficiencies under variable-returns-to-scale (VRS).

The data used to analyze the BES technology provides a unique opportunity to address measurements of efficiency at the farm-level exploring micro-oriented impacts that have not been studied in prior analyses. Specifically, the approaches apply a method allowing VRS technology to be analyzed using a Malmquist productivity index (MI) rather than the more commonly used assumption of CRS technology. To overcome numerical infeasibilities that arise in calculating the MI under VRS, a biennial Malmquist Index (BMI) is used similar to that proposed by Pastor, Asmild, and Lovell (2011). Allowing for VRS technology provides a way to compare farms to their contemporaries that are most similar to themselves. While the VRS technology is nested in the CRS technology (Färe et al., 1994), the BMI approach allows for examination of technological and efficiency changes with a decomposed MI considering farms compared to contemporaries more-similar to themselves than those to which they may be referenced under CRS assumptions.

1.2 Purpose and Objectives

The purpose of this study is to establish a framework to analyze on-farm efficiency impacts of adopting technology over time. This study uses panel data with information on BES adoption to allow for non-parametric approaches to estimate technical efficiency, revenue-constrained cost-efficiency, and Malmquist Indexes for 129 farms in Kansas using data from 1993 through 2011.

Specifically the objectives of the study are to:

1) Compare technical efficiency measures for the sample of farms under CRS and VRS assumptions and then examine the impact on technical efficiency of adoption of BES;

2) Compare the Malmquist index assuming CRS and the biennial Malmquist index under VRS (BMI_{VRS}) to assess the impact on productivity measures, and examine the impact on BMI_{VRS} and its decomposition into efficiency and technical change from BES adoption; and

3) Examine cost efficiency measures for the farms in the sample to assess from an input-orientation the impacts on calculated cost-effectiveness, traditional cost efficiency, and output mix efficiency observed under CRS and VRS and from adopting BES technologies.

Multiple non-parametric models with multiple inputs and outputs are considered to examine on-farm efficiency impacts of BES. Outputs include corn, soybeans, sorghum, wheat, and other crop production. Inputs include categories for labor, direct inputs, maintenance, energy, and general inputs.

We calculate technical efficiency measures from a non-parametric approach using data envelopment analysis (DEA) under both CRS and VRS technologies. Technical efficiency results under VRS technology (TE_{VRS}) are then analyzed using regression analysis with multiple independent variables to assess the impact of adoption of BES.

Malmquist productivity indexes (MI) are calculated using a non-parametric DEA approach developed by Färe, Grosskopf, Norris, and Zhang (1994). We then include an analysis of the productivity, technical change and efficiency changes associated with BES under CRS using a traditional MI and under VRS technology assumptions using the biennial Malmquist Index (BMI) developed by Pastor, Asmild, and Lovell (2011). Results from these analyses are tested to examine if: (1) the MI and BMI and their respective decompositions into technology and efficiency changes are equivalent; (2) if the underlying distributions for BMI_{VRS}, technology and efficiency changes are the same for adopters and non-adopters of BES across the biennial timeframes, and (3) has BES adoption affected productivity, technical change, and efficiency change.

A cost-effectiveness (revenue-indirect cost efficiency), traditional cost efficiency, and output mix efficiency analyses are performed on the farms similar to in Camanho and Dyson (2005) and Thanassoulis, Portela, and Despić (2008). The differences from assuming CRS and VRS technologies are considered. This input-oriented analysis provides insights into the estimated ability of the sample farms to produce their observed levels of revenue while minimizing costs – indirectly maximizing profits. The ability of farms to produce observed levels of outputs at minimal cost; and the level of cost-savings that can be found beyond traditional cost efficiency analysis by allowing output levels to alter while achieving observed levels of revenue is examined.

1.3 Organization of the Study

The remainder of the dissertation is organized in the following manner. Chapter 2 provides a brief review of efficiency theory and techniques considered in this analysis and the methods for analyzing the efficiency impacts of BES. A review of existing literature focusing on efficiency impacts of BES is included. Chapter 3 examines the unique data that was obtained for the study of BES on the sample of Kansas farms – including a novel approach to the application of indexing input prices for the crop mixes among the sample farms. Chapter 4 features the technical efficiency measures estimated for the sample farms under CRS and VRS DEA models. Analysis of the VRS measures was used to estimate the impacts of BES adoption using regression. Chapter 5 examines productivity changes estimated for the sample panel using a MI with the commonly used CRS framework and compare the results with those of an alternative framework allowing for VRS technology using a BMI. The results of the BMI VRS model compares BES adopters to non-adopters via a series of statistics examining the distribution of results of the BMI statistic, the biennial efficiency change (BEC), and the biennial technology change (BTC). Chapter 6 examines the results of analyzing cost effectiveness (Revenue-Indirect Cost Efficiency) under CRS and VRS; and then analyzes the impact of adopting biotechnology enhanced soybeans on cost efficiency, traditional cost efficiency, and output mix efficiency measures. Chapter 7 presents conclusions, policy implications, and suggestions for future work regarding BES technology and future technology analyses.

Chapter 2 - Efficiency Analysis and Application to BES Adoption

This chapter reviews the theory and techniques that are directly related to the analyses in this study of BES adoption. The intent is not to present a full review of the broad subject matter of efficiency, but rather to provide the relevant background from which this study builds.

This chapter outlines how the study was designed with specific goals to:

1) Analyze the impacts of BES adoption by examining measurements of technical efficiency calculated both under constant returns-to-scale and variable returns-to-scale technologies; and use regression analysis to test for impacts of adopting BES on production efficiency;
2) Compare the Malmquist productivity index assuming constant returns-to-scale with the biennial Malmquist index assuming variable returns-to-scale and their respective decompositions into efficiency change and technical change to examine if there is any difference in the distributions from which they are drawn; and to assess if there is a significant impact of the constant returns-to-scale and variable returns-to-scale assumptions in considering BES adoption;
3) Use cost-minimizing constrained problems to examine the cost efficiency measures of cost-effectiveness; traditional cost efficiency; and output mix efficiency obtained for the farms to examine if there is an impact on the measurements from the adoption of biotechnology enhanced soybeans; and
4) Consider the previous analyses of BES and efficiency estimation to build upon this body of literature.

The following sections outline how these measurements were made and analyze the impacts of BES adoption on-farm efficiency and productivity.

2.1 Returns-to-Scale and Modeling Assumptions

The assumptions of constant-returns-to-scale (CRS) and variable-returns-to-scale (VRS) concerning production technology have been identified as a root of disagreement and usefulness in multiple analyses of efficiency. Färe et al. (1994) used the geometric means of two Malmquist productivity indexes (MI) to examine the productivity growth of a sample of OECD countries using a non-parametric programming technique assuming CRS. They also incorporated the use of VRS assumptions in calculating specific distances to their efficient frontier for decomposing the MI. Ray and Desli (1997) commented on the Färe et al. (1994) work pointing out the "problem of internal consistency" due to mixing of measurements obtained under VRS and CRS and that "[r]emarkably different conclusions follow when one consistently uses a VRS technology as a benchmark (p. 1039)" when compared to assuming CRS technology, especially when the underlying true technology satisfies VRS. Färe, Grosskopf, and Norris (1997) in their reply to Ray and Desli (1997) argue that "[b]y construction, these technologies are nested: the CRS technology "contains" the VRS technology (p. 1040)." Färe, Grosskopf, and Norris inferred that the analyses under CRS and VRS technologies do not require that the data satisfy either, but rather form an "alternative benchmark". Ray and Desli agreed the use of both CRS and VRS assumptions is valid even when VRS was the actual technology in computing specific items such as the overall MI – but challenged the decomposition of the MI using mixed returns-to-scale.

Farrell (1957) used data from U.S. agriculture to develop his illustration for examining measures of technical efficiency. He pointed out that "[a]t the least, one would need to make a detailed attempt to allow for the heterogeneity of land inputs, before one could draw more than the roughest inferences about American agricultural efficiency (p. 266)."

Coelli et al. (2005) point out that CRS assumptions are appropriate when “all firms are operating at an optimal scale. However, imperfect competition, government regulations, constraints on finance, etc., may cause a firm to be not operating at optimal scale (p. 172).”

Assuming a VRS technology in the efficiency analysis of farms that have short-term fixed land bases and heterogeneity in land inputs results in sample farms benchmarked to operations more similar to themselves (at least in size) than under CRS. This benchmarking to firms of similar size is due to the nature of the tighter envelopment of data observations with convexity constraints under VRS than when CRS is assumed (Coelli et al., 2005). Given the reasons above, we assume VRS assumptions can provide benefits in the analysis of on-farm productivity and efficiency examining the adoption of biotechnology enhanced soybeans (BES).

For the majority of the models and analyses in this study, an output-orientation toward efficiency analyses is used given the focus on BES. Examining efficiency from an output perspective enables a focus on the assessment of the use of current resources in producing outputs (Camanho and Dyson, 2005). The nature of the heterogeneous fixed inputs (land) in crop production lends to a consideration of the increased output from a set of inputs represented by an output-oriented framework. The cost-minimization revenue-constrained problem presented in section 2.4 and subsequent results in Chapter 6 are the exception where the input-orientation is used seeking the input-mix that minimizes costs to meet an output-mix that satisfies a revenue constraint.

2.2 Technical Efficiency

Technical efficiency under output-orientation measures the amount by which outputs could proportionately be increased while maintaining the same level of inputs. This study will follow the approach for measuring technical efficiency laid out in Färe et al. (1994) and Coelli et al. (2005) considering the distance formulas from observed points to the efficient frontier (or boundary) to which an observation may be compared in representing technical efficiency.

Technical efficiency measures for a set of sample farms under CRS and VRS assumptions are compared empirically. Regression analysis of the technical efficiency measures under VRS (TE_{VRS}) will then be presented to estimate the impacts of adoption of BES.

2.2.1 Technical Efficiency CRS vs. VRS

Färe et al. (1994) makes use of the multiplicative inverse relationship between the output-based Farrell measure of technical efficiency and the output distance function using non-parametric programming techniques – specifically data envelopment analysis (DEA). Following Färe et al. (1994), this study assumes there are $j = 1,\ldots,129$ farms using $n = 1,\ldots,N$ inputs $x_{n,j}^{t}$ at each time period $t = 1,\ldots T$. These inputs are used to produce $m = 1,\ldots,M$ outputs $y_{m,j}^{t}$ at time period t. Under the CRS technology assumption, technical efficiency (TE_{CRS}) may be found for decision making unit (DMU) j' by solving the linear programming problem (1) – in our case separately for each farm j' in period t where $D_{O,CRS,j'}^{t}({x^{t}}_{j'},{y^{t}}_{j'})$ is the measured TE_{CRS}.

(1) $[D_{O,CRS,j'}^{t}({x^{t}}_{j'},{y^{t}}_{j'})]^{-1} = \ max\ \theta_{CRS,j'}^{t}$

subject to:

$\sum_{j=1}^{129}[\lambda_{j}^{t}x_{n,j}^{t}] \leq x_{n,j'}^{t},\ n = 1,\ldots,N$

$\sum_{j=1}^{129}[\lambda_{j}^{t}y_{m,j}^{t}] \geq \Theta_{CRS,j'}^{t}{y^{t}}_{m,j'},\ m = 1,\ldots,M$

$\lambda_{j}^{t} \geq 0, j = 1, \ldots, 129$

Assuming VRS technology, technical efficiency (TE_{VRS}) may be found solving a similar linear programming problem to (1), but with the addition of a convexity assumption that all (λ_j^t) in a single period *t* across all farms (*j*) sum to 1 when optimizing problem (2) for each farm in period t.

(2) $[D^t_{O,VRS,j'}(x^t_{j'}, y^t_{j'})]^{-1} = \ max\ \theta^t_{VRS,j'}$

subject to:

$\sum_{j=1}^{129}[\lambda_j^t x_{n,j}^t] \leq x^t_{n,j'},\ n = 1,\ldots,N$

$\sum_{j=1}^{129}[\lambda_j^t y_{m,j}^t] \geq \Theta^t_{VRS,j'} y^t_{m,j'},\ m = 1,\ldots,M$

$$\sum_{j=1}^{129}[\lambda_j^t] = 1$$

$\lambda_j^t \geq 0, j = 1, \ldots, 129$

2.2.2 Analyzing On-Farm Impacts of BES with Regression of TE_{VRS}

A linear regression analysis is used to examine the impact on observed TE_{VRS} measures considering the binary (0,1) variable [ADOPT] as a regressor. $ADOPT_t$ equals 1 if the farm had adopted BES in period *t* or in a prior year of the analysis, and equal to 0 otherwise. The other independent variables in the linear regression analysis include a binary (0,1) dummy variable accounting for a statewide impact incident between 1993 and 2011. The variables W95, W00, W02, W03, and W11 are yearly dummy variables equal to 1 in 1995, 2000, 2002, 2003 and 2011, and 0 otherwise, respectively. These are the years when a statewide negative yield event occurred with at least one of the primary crops (corn, soybeans, sorghum, or wheat) experiencing a statewide average yield per acre that was less than 80% of the preceding five-year moving average as reported by USDA-NASS (USDA-NASS, Quick Stats). A trend was also included in the regression, as well. The coefficient estimate on ADOPT is analyzed to examine the impact of BES adoption on TE_{VRS} efficiency scores obtained. A censored (between 0 and 1) regression or TOBIT model is used to estimate as well to test the robustness of the results. This result provides an estimate of the impact of adopting BES for a farm's technical efficiency measure – providing an estimate of the potential production output level differences that would be expected corresponding to any significant positive impact on the efficiency measures expected.

2.3 Malmquist Index

Färe, Grosskopf, Norris, and Zhang (1994) proposed a measure of the Malmquist index of total factor productivity growth (MI) derived with non-parametric programming methods using distance formulas to decompose productivity into a product of technical change and efficiency change (catching up). This study explores the MI, technical change, and efficiency change measures of the MI_{CRS} following Färe et al. (1994). Given the linear-programming (numerical) infeasibilities that arise in MI models assuming VRS, the alternative Biennial Malmquist Index (BMI) approach as proposed by Pastor, Asmild, and Lovell (2011) is estimated.

The MI is useful in examining economies as demonstrated by Färe et al. (1994) and Pastor, Asmild, and Lovell (2011). Other analyses have used the non-parametric techniques to examine national economies (Coelli and Rao, 2005; Deb and Ray, 2013). Coelli and Rao (2005) examined the agricultural output and productivity of 93 countries following Färe et al. (1994). Deb and Ray (2013) use the BMI of Pastor, Asmild, and Lovell to examine inter-state productivity growth following economic reforms in India.

A method to compare the MI_{CRS} and BMI assuming VRS and their respective decompositions for identifying if there is a difference between the underlying distributions was used. The BMI_{VRS} results for BES adopters and non-adopters is examined to discover if the underlying distributions for the BMI and decompositions into technical change and efficiency changes differed, potentially indicating a significant impact of BES technology adoption. When a significant impact of adoption is found, further analysis following the methods of comparison between the target groups is used (Färe et al., 1994 and Pastor, Asmild, and Lovell, 2011).

2.3.1 Malmquist Index – CRS

Färe et al. (1994) apply non-parametric techniques for MI productivity growth analysis to a sample of OECD countries allowing them to decompose the MI into the components of technical change and efficiency change.

Färe et al. (1994) use four linear-programming problems to calculate the MI under CRS between periods *t* and *t+1* for DMU j'. These include equation (1) we saw earlier for the CRS, as well as additional equations (3), (4), and (5) that are discussed below.

(1) $D_{O,CRS}^{t}(x_{j'}^{t}, y_{j'}^{t})$

(3) $D_{O,CRS}^{t+1}(x_{j'}^{t+1}, y_{j'}^{t+1})$

(4) $D_{O,CRS}^{t}(x_{j'}^{t+1}, y_{j'}^{t+1})$

(5) $D_{O,CRS}^{t+1}(x_{j'}^{t}, y_{j'}^{t})$

Problem (1) was seen in section 2.2.1 earlier to calculate the TE_{CRS} measure for farm j'. The computation for problem (3) is the same as problem (1) with the data for the period *t+1* substituted for period *t*. So the linear programming problem (3) for farm j' is represented as:

(3) $[D_{O,CRS,j'}^{t+1}(x_{j'}^{t+1}, y_{j'}^{t+1})]^{-1} = \ max\ \theta_{CRS,j'}^{t+1}$

subject to:

$$\sum_{j=1}^{129}[\lambda_j^{t+1}x_{n,j}^{t+1}] \le x_{n,j'}^{t+1}, n = 1, \dots, N$$

$$\sum_{j=1}^{129}[\lambda_j^{t+1}y_{m,j}^{t+1}] \ge \Theta_{CRS,j'}^{t+1}y_{m,j'}^{t+1}, m = 1, \dots, M$$

$\lambda_j^{t+1} \ge 0, j = 1, \dots, 129$

The other two linear programming problems needed to compute the MI for farm j' are represented in problems (4) and (5) and each involve information from two periods.

(4) $[D_{O,CRS,j'}^{t}(x_{j'}^{t+1}, y_{j'}^{t+1})]^{-1} = \ max\ \theta_{CRS,j'}$

subject to:

$$\sum_{j=1}^{129}[\lambda_j^{t}x_{n,j}^{t}] \le x_{n,j'}^{t+1}, n = 1, \dots, N$$

$$\sum_{j=1}^{129}[\lambda_j^{t}y_{m,j}^{t}] \ge \Theta_{CRS,j'}y_{m,j'}^{t+1}, m = 1, \dots, M$$

$\lambda_j^{t} \ge 0, j = 1, \dots, 129$

The final linear programming problem, problem (5), is similar to problem (4) - but the *t* and *t+1* references are transposed.

(5) $[D^{t+1}_{O,CRS,j'}(x^{t}_{j'}, y^{t}_{j'})]^{-1} = \ max\ \theta_{CRS,j'}$

subject to:

$$\sum_{j=1}^{129}[\lambda_j^{t+1} x_{n,j}^{t+1}] \leq x^{t}_{n,j'}\ , n = 1, \dots , N$$

$$\sum_{j=1}^{129}[\lambda_j^{t+1} y_{m,j}^{t+1}] \geq \Theta_{CRS,j'} y^{t}_{m,j'}\ , m = 1, \dots , M$$

$\lambda_j^{t+1} \geq 0, j = 1, \dots ,129$

The MI is determined for each farm according to the technique in Färe et al. (1994) as:

(6) $M_{O,CRS}(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{D^{t+1}_{O,CRS}(x^{t+1}, y^{t+1})}{D^{t}_{O,CRS}(x^{t}, y^{t})} \times \left[\left(\frac{D^{t}_{O,CRS}(x^{t+1}, y^{t+1})}{D^{t+1}_{O,CRS}(x^{t+1}, y^{t+1})}\right)\left(\frac{D^{t}_{O,CRS}(x^{t}, y^{t})}{D^{t+1}_{O,CRS}(x^{t}, y^{t})}\right)\right]^{1/2}$.

Efficiency change (EC) is the ratio of TE_{CRS} in period *t+1* to the TE_{CRS} in period t, the portion of the MI_{CRS} outside the brackets as identified in equation (7). This is the change in relative efficiency of the DMU represented as the ratio of the distances between the observed production and the efficient frontier (maximum potential production) in each respective period. That is:

(7) $EC_{O,CRS}(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{D^{t+1}_{O,CRS}(x^{t+1}, y^{t+1})}{D^{t}_{O,CRS}(x^{t}, y^{t})}$.

The technical change (TC) is the geometric mean of the two ratios inside the brackets of the MI_{CRS} formula (6). TC is represented in equation (8).

(8) $TC_{O,CRS}(x^{t+1}, y^{t+1}, x^t, y^t) = \left[\left(\frac{D^t_{O,CRS}(x^{t+1}, y^{t+1})}{D^{t+1}_{O,CRS}(x^{t+1}, y^{t+1})}\right)\left(\frac{D^t_{O,CRS}(x^t, y^t)}{D^{t+1}_{O,CRS}(x^t, y^t)}\right)\right]^{1/2}$

Technical change is the geometric mean of 1) the ratio of the distance of the DMU observation in period *t+1* from the frontier formed by the observations in period *t* to the distance of the observation in period *t+1* from the frontier formed by the observations in period *t+1*; and 2) the ratio of the distance of the DMU observation in period *t* to the frontier formed by the observations in period *t* to the distance of the observation in period *t* from the frontier formed by the observations in period *t+1*. Each ratio in equation (8) compares distances between a constant observation from a single period to two frontiers. Thus, each ratio compares the relative change in distance from the constant observation to the efficient boundary over time from *t* to *t+1*. Rather than using a single year's observation to develop TC, the geometric mean of the two ratios allows for the change in distances to the efficient boundary to be compared for each period's observation in the analysis. As long as there is technological progress (regress), the efficient boundary is pushed outward (inward) and the distance from each year's observation should not be closer to (further from) the period *t+1* boundary than it was to the boundary formed from the period t. Thus, TC provides an indicator of the impact of technical change between the periods which results in a shift of the efficient boundary between the two time periods.

2.3.2 Malmquist Index – VRS

Chen (2005) noted that applications of the Malmquist productivity indexes when assuming VRS do not usually include results nor "mention the occurrence of infeasibility (p. 550)." The numerical infeasibilities that arise with VRS assumptions in computing MI following Färe et al. (1994) result from convexity restrictions that result in comparing DMUs to similar size DMUs on the frontier. When an efficient DMU is observed in one period, but there is not a similar DMU in the other period being analyzed for the TC portion of the MI decomposition to which it may be compared on the efficient frontier, a numerical infeasibility occurs in solving the linear programming problem. The numerical infeasibility with the MI under VRS is similar to the infeasibility problem with super-efficiency analyses under returns-to-scale other than CRS when removing an efficient farm from those that are efficient and there is not another farm remaining for which to compare that farm. For an examination of the necessary and sufficient conditions for super-efficiency infeasibility to occur, see Seiford and Zhu (1999).

Chen (2005) resolved infeasibility occurrences under VRS with super-efficiency problems. However, the direct linkage to DEA-based Malmquist productivity analysis was not shown. Chen's method for resolving super-efficiency infeasibilities revolved around estimating several more models under input- and output- orientations and potentially turned to the more computationally simplistic assumption of CRS when VRS assumptions under input and output orientations were infeasible (Cook and Seiford, 2009). Furthermore, Chen compared the results that are based on the relative relationships between super-efficient observed firms with no clear technique presented for application to a MI-type problem.

The MI is modeled as proposed by Färe et al. (1994), but with a VRS assumption throughout. The MI model is examined for numerical infeasibilities. MI_{VRS} requires four linear programming problems to be solved in this analysis. The first is (2) from section 2.2.1 for the TE_{VRS}.

(2) $[D^t_{O,VRS,j'}(x^t_{j'}, y^t_{j'})]^{-1} = max\ \theta^t_{VRS,j'}$

The linear programming problem (9) is similar to problem (2), but with the substitution of *t+1* for each of the *t* period references.

(9) $[D^{t+1}_{O,VRS,j'}(x^{t+1}_{j'}, y^{t+1}_{j'})]^{-1} = \ max\ \theta^{t+1}_{VRS,j'}$

subject to:

$$\sum_{j=1}^{129}[\lambda^{t+1}_j x^{t+1}_{n,j}] \leq x^{t+1}_{n,j'}\ , n = 1, \dots, N$$

$$\sum_{j=1}^{129}[\lambda^{t+1}_j y^{t+1}_{m,j}] \geq \Theta^{t+1}_{VRS,j'} y^{t+1}_{m,j'}\ , m = 1, \dots, M$$

$$\sum_{j=1}^{129}[\lambda^{t+1}_j] = 1$$

$$\lambda^{t+1}_j \geq 0, j = 1, \dots, 129$$

The next two linear programming problems needed to calculate the MI_{VRS} are problems (10) and (11) – the cross-period VRS counterparts to (4) and (5), respectively. These VRS DEA linear programming problems each have the convexity restriction that the weights of the farms forming the references on the efficient boundary for each farm j sum to 1.

(10) $[D^{t}_{O,VRS,j'}(x^{t+1}_{j'}, y^{t+1}_{j'})]^{-1} = \ max\ \theta_{VRS,j'}$

subject to:

$$\sum_{j=1}^{129}[\lambda^{t}_j x^{t}_{n,j}] \leq x^{t+1}_{n,j'}\ , n = 1, \dots, N$$

$$\sum_{j=1}^{129}[\lambda^{t}_j y^{t}_{m,j}] \geq \Theta_{VRS,j'} y^{t+1}_{m,j'}\ , m = 1, \dots, M$$

$$\sum_{j=1}^{129}[\lambda^{t}_j] = 1$$

$$\lambda^{t}_j \geq 0, j = 1, \dots, 129$$

(11) $[D^{t+1}_{O,VRS,j'}(x^{t}_{j'}, y^{t}_{j'})]^{-1} = \ max\ \theta_{VRS,j'}$

subject to:

$$\sum_{j=1}^{129}[\lambda_j^{t+1} x_{n,j}^{t+1}] \leq x^{t}_{n,j'}\ , n = 1, \dots, N$$

$$\sum_{j=1}^{129}[\lambda_j^{t+1} y_{m,j}^{t+1}] \geq \Theta_{VRS,j'} y^{t}_{m,j'}\ , m = 1, \dots, M$$

$$\sum_{j=1}^{129}\left[\lambda_j^{t+1}\right] = 1$$

$$\lambda_j^{t+1} \geq 0, j = 1, \dots, 129$$

As found in other studies where computations of the decomposed MI under VRS assumptions resulted in numerical infeasibilities (Ray and Desli, 1997; Chen, 2005), the data in this study of 129 Kansas farms resulted in infeasibilities for TC and MI when analyzed consistently assuming VRS technology.

This study resolves the linear-programming (numerical) infeasibilities that arise in the MI models assuming VRS through the implementation of an alternative biennial Malmquist Index proposed by Pastor, Asmild, and Lovell (2011).

2.3.3 Biennial Malmquist Index

It is not singularly the potential “internal inconsistencies” that Ray and Desli (1997) noted that drive the uses of the biennial Malmquist Index (BMI). The numerical infeasibilities that are encountered with a typical MI decomposition as proposed by Färe et al. (1994) under VRS are often encountered (Chen, 2005; Färe et al., 1997).

Pastor, Asmild, and Lovell (2011) identified that "being forced to tell that story [about contributions of various drivers to productivity change] on the basis of a feasible subset of the data, not because of inadequacies in the data, but due to a shortcoming of the analytical technique, diminishes the credibility of the story (p. 14)." Faced with estimating efficiency measures by assuming CRS due to computational simplicity or looking for a method that can overcome the numerical infeasibilities while maintaining the usefulness of the MI – this study adopted the biennial Malmquist Index (BMI) to examine the data under VRS technology.

Pastor, Asmild, and Lovell (2011) developed the BMI partly as a method to solve the infeasibility issues confounding VRS technology analyzed with the MI. This is based off a Global Malmquist Index proposed by Pastor and Lovell (2005). Other shortcomings, such as computational difficulties may arise when adding an additional period into the analysis that can alter the comparison of two other periods that were previously examined. Pastor, Asmild, and Lovell highlight the ability of the biennial MI analysis to account for technical regress, unlike other non-parametric MI alternatives proposed following Färe et al. (1994). For example, Shestalova (2003) termed a sequential MI with a frontier composed of the current and all prior periods in their analysis.

Building from the MI analysis of Coelli et al. (2005) and Färe et al. (1994), the implementation of a BMI contributes to the consideration of the MI, efficiency change, and technical change under VRS assumptions resolving the numerical infeasibilities in computations. That is, the problem directly incorporates both technical efficiency and productivity analyses into one temporal problem. A significant alteration (clarification) from Pastor, Asmild, and Lovell (2011) should be noted from their basic construct of the VRS technology definition and subsequent construct of the "classic distance functions." Here we explicitly impose that in the linear programming problems used to develop the distance function representing the efficiency measure for each individual farm, the sum of all weights for every reference farm from both years in the biennial period on the efficient biennial frontier must sum to one. This constraint is not explicitly stated by Pastor, Asmild, and Lovell – rather it is inferred by the construct of the biennial technology definition being formed of the convex hull of the technology representing each of the years in the biennial reference period. This restriction on the weights for the reference farms in every biennial period is required to allow for calculation of the distance function that represents the level of inefficiency for the sample farms to be able to reach the VRS frontier regardless of the observed year in the biennial period of the efficient reference farm(s). Without this constraint in the linear programming problem for the $\mathrm{BMI}_{\mathrm{VRS}}$, there would exist a greater potential for infeasible solutions to be encountered as with the more traditional non-parametric MI analysis.

Following Pastor, Asmild, and Lovell (2011), the $\mathrm{BMI}_{\mathrm{VRS}}$ is defined by:

(12) $M_v^B\left(x_j^t, y_j^t, x_j^{t+1}, y_j^{t+1}\right) = \frac{D_v^B\left(x_j^{t+1}, y_j^{t+1}\right)}{D_v^B\left(x_j^t, y_j^t\right)}.$

While the MI calculated by Färe et al. (1994) was a geometric mean of two ratios, the BMI uses a single ratio of measurements from two reference time periods for a DMU to an efficient frontier that is comprised of observations from both time periods.

Computing the $\mathrm{BMI}_{\mathrm{vrs}}$ in equation (12) requires solving two linear programming problems for each farm in the sample. They are contained in problems (13) and (14). However, the terms will likely take different values for each individual model estimated for each farm. Unlike the MI approach following Färe et al. (1994), the BMI for each farm in the sample during a single biennial time period (2-years) faces an efficient frontier that could potentially contain farms from periods t and $t+1$. Accordingly, the inputs $x_{n,j}^{t}$ and $x_{n,j}^{t+1}$ for all farms j = 1,…129 are available for considering optimal input mixes. The corresponding outputs $y_{m,j}^{t}$ and $y_{m,j}^{t+1}$ from all farms j = 1,…129 are potentially in the optimal output mix during the biennial period considered. Therefore, finding λ_j^t and λ_j^{t+1} must be considered jointly in the model. The linear programming problem in (13) considers a single farm's inputs and outputs in period t in comparison to the biennial efficient frontier.

(13) $[D_{v,j'}^{B}(x_j^t, y_j^t)]^{-1} = \ max\ \theta_{v,j'}^{B}$

subject to:

$$\sum_{j=1}^{129}[\lambda_j^t x_{n,j}^t + \lambda_j^{t+1} x_{n,j}^{t+1}] \leq x_{n,j}^t\ , n = 1, \dots, N$$

$$\sum_{j=1}^{129}[\lambda_j^t y_{m,j}^t + \lambda_j^{t+1} y_{m,j}^{t+1}] \geq \theta_{v,j'}^{B} y_{m,j'}^t\ , m = 1, \dots, M$$

$$\sum_{j=1}^{129}\left[\lambda_j^t + \lambda_j^{t+1}\right] = 1$$

$$\lambda_j^t \geq 0, j = 1, \dots, 129$$

$$\lambda_j^{t+1} \geq 0, j = 1, \dots, 129$$

The linear programming problem in (14) considers a single farm's input and output mix from time period $t+1$ in measuring the distance to the biennial efficient frontier. The biennial efficient frontier in problems (13) and (14) are the same when considering each farm within the sample for the same t and $t+1$ periods.

(14) $[D^{B}_{v,j'}(x^{t+1}_{j}, y^{t+1}_{j})]^{-1} = \ max\ \theta^{B}_{v,j'}$

subject to:

$$\sum_{j=1}^{129}[\lambda^{t}_{j}x^{t}_{n,j} + \lambda^{t+1}_{j}x^{t+1}_{n,j}] \leq x^{t+1}_{n,j'}\ , n = 1, \dots, N$$

$$\sum_{j=1}^{129}[\lambda^{t}_{j}y^{t}_{m,j} + \lambda^{t+1}_{j}y^{t+1}_{m,j}] \geq \Theta^{B}_{v,j'}y^{t+1}_{m,j'}\ , m = 1, \dots, M$$

$$\sum_{j=1}^{129}\left[\lambda^{t}_{j} + \lambda^{t+1}_{j}\right] = 1$$

$\lambda^{t}_{j} \geq 0, j = 1, \dots, 129$

$\lambda^{t+1}_{j} \geq 0, j = 1, \dots, 129$

To depict the changes in relative movement of the efficient frontier and changes in the efficiency of the sample farms relative to the frontier, Pastor, Asmild, and Lovell (2011) decompose the $\mathrm{BMI}_{\mathrm{vrs}}$ (M^{B}_{v}) into two factors: efficiency change, EC^{B}_{v}, and technical change, TC^{B}_{v}.

Efficiency change is defined under the $\mathrm{BMI}_{\mathrm{vrs}}$ by Pastor, Asmild, and Lovell (2011) in equation (15) as it would under the MI construct for VRS by Färe et al. (1994).

(15) $EC^{B}_{v} = \frac{D^{t+1}_{V}(x^{t+1}_{j}, y^{t+1}_{j})}{D^{t}_{V}(x^{t}_{j}, y^{t}_{j})} = EC_{v}$

The numerator of equation (15) is found by solving problem (9) in section 2.3.2. The denominator of (15) is found by solving problem (2) in section 2.2.1. These individual linear programming problems are solved in relation to a single year's data and a single year efficiency frontier – not the biennial efficient frontier.

The technical change factor, TC_V^B, is defined through its relationship as a component of the $\mathrm{BMI}_{\mathrm{VRS}}$ along with EC_v^B and is shown in equation (16).

$$\textbf{(16)}\ TC_v^B = \frac{M_v^B}{EC_v^B} = \frac{D_v^B(x_j^{t+1}, y_j^{t+1}) \big/ D_v^B(x_j^t, y_j^t)}{D_v^{t+1}(x_j^{t+1}, y_j^{t+1}) \big/ D_v^t(x_j^t, y_j^t)}$$

The technical change factor, TC_V^B, represents that portion of the productivity change not accounted for by the change in efficiency or "catching up" to the frontier as referred to by Färe et al. (1994). The TC_V^B provides an indicator of the impact of technical change between the two periods in the biennial period that results in a shift in the efficient boundary. Since the biennial Malmquist productivity index is the ratio of the distances between the biennial efficient boundary and the second-period's observed data and the first-period's observations, the TC_V^B represents the portion of that change from shifts in the relative boundary rather than the shift toward each sub-period's individual efficient boundary as measured by the efficiency change.

2.3.4 Constant Returns to Scale and Variable Returns to Scale for Malmquist Indices

A review of the literature examining non-parametric efficiency analysis raises questions regarding the appropriateness of assuming CRS technology when VRS may be the underlying true technology. CRS is selected as the default choice in analyses due to the numerical infeasibilities that arise when assuming VRS (Ray and Desli, 1997; Chen, 2005; and Pastor, Asmild, and Lovell, 2011). While this study has outlined techniques to address the infeasibilities that arise from assuming VRS, an examination of the impact of assuming CRS or VRS in the analysis is important.

Meyer and Rasche (1989) used a Kolmogorov-Smirnov goodness-of-fit hypothesis test (KS-test) to identify if a sample of observations (rate of return data) was the result of two different models – in their case an expected utility ordering model and a mean-standard deviation ranking function.

This study uses the two-sample KS-test with the null hypothesis that the empirical cumulative distribution functions each sample is drawn from are identically distributed. This two sample test is used to compare the model results of the MI_{CRS} and BMI_{VRS} and their respective decompositions into technical change and efficiency change. If the KS-test null hypothesis is rejected, following Meyer and Rasche (1989), we can conclude that there is evidence that the results under CRS and VRS using the MI_{CRS} and BMI_{VRS} measures are significantly different. Assuming VRS is the correct assumption, this would point toward a bias from assuming CRS.

The U.S. Department of Commerce - National Institute of Standards and Technology (NIST) in its *e-Handbook of Statistical Methods* includes a demonstration of the use of the two-sample t-test (T-test) determining if the population means of two samples are equal, citing that the test can be used to examine if one process is equivalent to another (NIST/SEMATECH, 2015). With the null hypothesis that the means are equal, if the null hypothesis is rejected, it is rejected that the two processes are equivalent.

To assess the level of bias (on average) that exists when assuming one return-to-scale technology (e.g., CRS), when the other return-to-scale assumption was correct (e.g., VRS), a two-sample t-test (T-test) is used to examine if the means of the empirical cumulative distribution functions from the MI_{CRS} and BMI_{VRS} and their respective decompositions into technical change and efficiency change are equal.

2.3.5 The Impact of BES on Productivity

Comparing impacts of BES adoption in the sample can be accomplished with the techniques as outlined in 2.3.4. Analyzing if a statistically significant difference exists between the empirical cumulative distribution function results associated with the BMI_{VRS} and its decomposition into the components of technical change and efficiency change for BES adopters and non-adopters can provide evidence of the impact from BES adoption on productivity.

The results obtained from modeling the BMI_{VRS}, technical change, and efficiency change are analyzed for differences between BES adopters and non-adopters in the empirical cumulative distribution functions of the groups using a Kolmogorov-Smirnov goodness-of-fit test. If the KS-test null hypothesis is rejected, there is evidence that the results of adopting BES or not adopting are significantly different.

The level of bias (on average) is assessed by examining the empirical cumulative distribution functions means with a T-test similar to that identified in section 2.3.4 following the NIST/SEMATECH (2005), but here adjusted using Satterthwaite's approximation due to the Behrens-Fisher problem design due to unknown and unequal variances in the samples. Scheffé (1970) cited multiple solutions to the Behrens-Fisher problem that arises when comparing the means of two populations when their variances are unknown. Brunner and Munzel (2000) indicated that the standard Satterthwaite-Smith-Welch (SSW) approximation used by most software packages to handle the Behrens-Fisher problem provides good results. Analysis of the identified results for BES adopters and non-adopters of changes in farm productivity, efficiency changes, and technology changes are examined for evidence of an impact from adoption of BES.

2.4 Cost Effectiveness, Cost Efficiency, and Output Mix Efficiency Analysis of BES

A cost-minimizing DEA approach was used to examine the optimal input mixes for each farm when (1) minimizing costs while maintaining at least the observed level of revenue earned by that farm and (2) minimizing costs while producing at least the observed level of each output. The nature of the first problem was termed a "revenue-indirect production technology" by Färe, Grosskopf, and Lovell (1994) where outputs could vary with a target revenue (Thanassoulis, Portela, and Despić, 2008). Camanho and Dyson (2005) used this framework but with the establishment of the target revenue of the DMU set at the observed level, referring to it as cost effectiveness. With revenue held constant (as in Camanho and Dyson (2005)) or allowed to increase as proposed in Thanassoulis, Portela, and Despić (2008); the impact of optimizing at a minimum cost is to maximize profits at the target revenue.

Analyzing the farms to seek a cost-minimizing level of inputs to produce at the observed level of outputs is the "traditional minimum cost model" Thanassoulis, Portela, and Despić (2008) cite as part of the decomposition of cost effectiveness following Camanho and Dyson (2005). Camanho and Dyson (2005) term this traditional minimum cost model simply as cost efficiency when divided by the observed costs. The cost efficiency measure is multiplied by the output mix efficiency measure to form cost-effectiveness. Output mix efficiency is a measure of the extent costs might be reduced beyond the traditional cost efficient level when output levels and mix are allowed to vary while maintaining the observed level of revenue.

2.4.1 Cost Effectiveness (Revenue-Indirect Cost Efficiency)

For this analysis, each farm – in each year – is compared with its contemporaries in the sample to seek a cost-minimizing input mix capable of producing observed outputs that reach a target revenue level. The revenue-constraint requires that each of the optimal cost-minimizing solutions also provides that the output level produced provides for at least as much revenue given observed output prices as was observed for each farm considered as the subject in the optimization problem.

The cost-minimization problem from an input-orientation perspective can provide insights into the least-cost manner of combining resources to produce a mix of outputs. In this analysis, we also constrain the optimal output mix to one that provides for the resulting revenue to be at least as much or more than achieved by the farm for each analyzed period. In this regard, the farms are not diminishing the cash-flow nor the net-profits since the revenues are at least as large, and the inputs are chosen to minimize costs. Minimizing the costs for which the level is obtained in the analysis while identifying a level of revenue allows for the indirect measurement of profit. When the revenue-constrained cost-minimizing results are divided by observed costs, the result is the revenue-indirect cost efficiency measure noted by Thanassoulis, Portela, and Despić (2008) or the cost effectiveness measure cited by Camanho and Dyson (2005).

2.4.1.1 Cost Effectiveness Under CRS and VRS

Both CRS and VRS assumptions are applied to measure cost effectiveness to examine the differences that might arise between the two assumptions. Cost effectiveness under CRS (CE_{CRS}) is found by solving the input-oriented revenue-constrained cost-minimization linear programming problem given by problem (17) and dividing the resulting minimized cost by the observed total input costs. Note that $P_{m,j'}^{t}$ is equal to the output prices for $y_{m,j'}^{t}$, and an optimal $y_{m,j'}^{**,t}$ is computed for each farm in this analysis so that the revenue ($\sum_{m=1}^{M} P_{m,j'}^{t} y_{m,j'}^{**,t}$) realized from the level of production computed as the cost-minimizing under input-orientation for each farm is at least as large as the observed revenue ($\sum_{m=1}^{M} P_{m,j'}^{t} y_{m,j'}^{t}$). Note that $w_{n,j'}^{t}$ is the input price for $x_{n,j'}^{t}$. An optimal $x_{n,c,j'}^{**,t}$ is computed for each farm in this analysis so that the costs are minimized in producing $y_{m,c,j'}^{**,t}$.

(17) $min\, TC_c = \sum_{n=1}^{N} \left[w_{n,j'}^{t} x_{n,c,j'}^{**,t} \right]$

subject to:

$\sum_{j=1}^{129} [\lambda_j^t x_{n,j}^t] \le x_{n,c,j'}^{**,t}$, $n = 1,\ldots,N$

$\sum_{j=1}^{129} [\lambda_j^t y_{m,j}^t] \ge y_{m,c,j'}^{**,t}$, $m = 1,\ldots,M$

$$\sum_{m=1}^{M} P_{m,j'}^{t} y_{m,c,j'}^{**,t} \ge \sum_{m=1}^{M} P_{m,j'}^{t} y_{m,j'}^{t}$$

$\lambda_j^t \ge 0, j = 1, \ldots, 129$

Thus,

(18) Cost-Effectiveness$_{CRS}$ $= \frac{\sum_{n=1}^{N}\left[w_{n,j'}^{t} x_{n,c,j'}^{**,t}\right]}{\sum_{n=1}^{N}\left[w_{n,j'}^{t} x_{n,j'}^{t}\right]}$.

Cost efficiency under VRS (CE_{VRS}) is found by solving the input-oriented revenue-constrained cost-minimization linear programming problem in (19) and dividing the resulting minimized cost by the observed total input costs. The linear programming problem in (19) is similar to that in problem (17) – with the addition of a convexity constraint on the weights on the farms. An optimal $x_{n,v,j'}^{**,t}$ is computed for each farm in this analysis so that the costs are minimized in producing $y_{m,v,j'}^{**,t}$. The optimal solution provides for producing revenue level ($\sum_{m=1}^{M} P_{m,j'}^{t} y_{m,v,j'}^{**,t}$) realized from the level of production under input-orientation so that each farm can generate revenue at least as large as the observed revenue ($\sum_{m=1}^{M} P_{m,j'}^{t} y_{m,j'}^{t}$).

(19) $min\ TC_v = \sum_{n=1}^{N}\left[w_{n,j'}^{t} x_{n,v,j'}^{**,t}\right]$

subject to:

$\sum_{j=1}^{129}[\lambda_j^t x_{n,j}^t] \leq x_{n,v,j'}^{**,t}$, $n = 1,\ldots,N$

$\sum_{j=1}^{129}[\lambda_j^t y_{m,j}^t] \geq y_{m,v,j'}^{**,t}$, $m = 1,\ldots,M$

$$\sum_{j=1}^{129}\left[\lambda_j^t\right] = 1$$

$$\sum_{m=1}^{M} P_{m,j'}^{t} y_{m,v,j'}^{**,t} \geq \sum_{m=1}^{M} P_{m,j'}^{t} y_{m,j'}^{t}$$

$\lambda_j^t \geq 0, j = 1, \ldots, 129$

Thus,

(20) Cost-Effectiveness$_{VRS} = \frac{\sum_{n=1}^{N}\left[w_{n,j'}^{t} x_{n,v,j'}^{**,t}\right]}{\sum_{n=1}^{N}\left[w_{n,j'}^{t} x_{n,j'}^{t}\right]}$.

2.4.2 Traditional Cost Efficiency

The cost-minimization problem from an input-orientation perspective can provide insights into the least-cost manner of combining resources to produce a mix of outputs. This is accomplished by constraining the cost-minimization problem to produce at least the same level of each output that was observed. The problem in (21) is the linear programming problem assuming variable returns-to-scale technology.

(21) $min\, TC_V = \sum_{n=1}^{N}\left[w_{n,j'}^{t} x_{n,v,j'}^{*,t}\right]$

subject to:

$\sum_{j=1}^{129}[\lambda_j^t x_{n,j}^t] \leq x_{n,v,j'}^{*,t}$, $n = 1,\ldots, N$

$\sum_{j=1}^{129}[\lambda_j^t y_{m,j}^t] \geq y_{m,j'}^{t}$, $m = 1,\ldots,M$

$$\sum_{j=1}^{129}[\lambda_j^t] = 1$$

$\lambda_j^t \geq 0, j = 1, \ldots, 129$

The traditional cost efficiency measure is calculated using the results from problem (21) in equation (22).

(22) Cost-Efficiency$_{VRS} = \frac{\sum_{n=1}^{N}\left[w_{n,j'}^{t} x_{n,v,j'}^{*,t}\right]}{\sum_{n=1}^{N}\left[w_{n,j'}^{t} x_{n,j'}^{t}\right]}$.

The cost-efficiency measure developed in (22) indicates the percentage of the observed cost to which the individual farm is estimated to be able to decrease their costs in producing the same level of outputs. A farm with a cost-efficiency measure of 1 is considered fully cost-efficient and is producing their outputs at the lowest costs.

2.4.3 Output Mix Efficiency

Output mix efficiency provides an indication of the level costs may be reduced below the levels found in the cost-efficiency analysis (from problem (21)) by allowing output mix to alter while maintaining the observed revenue levels as in the cost-effectiveness analysis (from problem (19)) (Camanho and Dyson, 2005). Camanho and Dyson (2005) obtained the output mix efficiency as a residual of the relationship in (23) after finding the cost-effectiveness and cost-efficiency measures.

(23) Cost-Effectiveness = (Output Mix Efficiency) × (Cost-Efficiency)

Output mix efficiency may also be found more directly by the relationship in (24) combining the results of problem (19) and problem (21).

(24) Output Mix Efficiency $= \frac{\sum_{n=1}^{N}\left[w_{n,j'}^{t}, x_{n,v,j'}^{**,t}\right]}{\sum_{n=1}^{N}\left[w_{n,j'}^{t}, x_{n,v,j'}^{*,t}\right]}.$

2.4.4 Comparison of BES Adopters and Non-Adopters for Cost Effectiveness

The measurements under (18) and (20) are summarized and the results for BES adopters and non-adopters are compared for the years following the commercial introduction of BES. Distribution of sample farms across defined levels of cost effectiveness measures are presented for each group. Examining the average cost effectiveness scores for adopters and non-adopters of BES we identify the difference in the estimated levels that the groups of farms could reduce costs if they were fully efficient in the use of the inputs to achieve the level of observed revenues (Camanho and Dyson, 2005).

Regression analyses similar to that outlined in section 2.2.2 are used to analyze the impact of biotechnology enhanced soybean adoption on cost-effectiveness, cost-efficiency, and output mix efficiency assuming variable returns-to-scale.

2.5 Previous Analyses of BES Impact on Efficiency

While advantages in efficiencies for obtaining off-farm income to those implementing BES in their management programs has been identified, direct improvements in on-farm efficiencies have not been cited (Fernandez-Cornejo, 2007). While USDA Agricultural Resource Management Survey (ARMS) data for representative cross-sectional sampling in evaluating BES efficiency has been used in analyses such as Fernandez-Cornejo (2007) and Goodwin and Mishra (2004), an analysis of farm-level efficiency using continuous panel data allows for more insight into efficiency changes over time that coincide with the adoption of this technology. Furthermore, the availability of adoption information overlaid with farm-level panel data allows for the relationship of farms to the efficient frontier as well as the movement of the frontier to be considered.

2.5.1 BES and Efficiency on a Macro-Scale

Analyses have been done on a macro-scale examining the impact of BES on the efficiency of soybean production. As noted, several of the methods for examining efficiency were developed to look at national level efficiency measures.

Zhang and Xue (2007) analyzed the ability of China to supply its growing demand for soybeans developing non-parametric efficiency analyses using DEA techniques. Specifically they developed output-oriented measurements of technical efficiency and scale efficiency under VRS and CRS assumptions, and then a Malmquist productivity index (MI) looking at soybean production in China. The identified output for this analysis was soybeans with the four inputs being seed, labor, machine cost, and fertilizer quantity. Cross-sectional data were used for the technical efficiency and scale efficiency measures. A different panel data set was used for computing the MI. Each of the datasets was an average over provinces in China – not identified as individual farms.

While Zhang and Xue (2007) did not include information on the use of BES in their analysis, they did refer to the need for GM soybeans to be imported into China to meet demand. The lack of GM soybean adoption was cited by Zhang and Xue (2007) commenting that "…China's soybean production may not be able to improved substantially in recent years because of China's non-GM soybean policy (p.100)."

2.5.2 USDA-ERS Analyses of BES Efficiency Impacts at the Farm-Level

Economists working with USDA's Economic Research Service (ERS) have analyzed efficiency impacts from BES for farms in various manners. The primary impacts have generally been related to the increases in off-farm income for farm households rather than any positive impact for on-farm efficiency – other than labor being applied to off-farm pursuits. Although balanced panel data have not been available to ERS, they have provided focus on BES and on-farm technology adoption in general using a significant data source on American agriculture: Agricultural Resource Management Survey (ARMS) project.

Smith (2002) sought to distinguish if "smart farming" (the use of more management-intensive practices that could potentially substitute for capital-intensive activities) was diminished by off-farm employment. Noting the greater level of off-farm labor supply from farm households, Smith proposed methods to explore the value of changes in technology adoption or management practices such as using off-farm prevailing wage rates to value management time on-farm or examining net returns of a farm household's total income rather than only income from farm activities. Specifically considering herbicide-tolerant soybeans, Smith identified that on-farm financial returns alone may not account for increased off-farm employment available with time savings due to BES, which increases the opportunity costs that need to be applied to time spent on farm management.

Goodwin and Mishra (2004), inspired by Smith's (2002) questions regarding the extent off-farm work has on farm efficiency, examine the relationship between farm efficiency and off-farm labor supply. Using data from USDA's 2001 NASS ARMS project with 7,699 farms probability-weighted in a stratified survey, Goodwin and Mishra constructed measures of farms' overall efficiency. They defined the on-farm efficiency as gross cash income over total variable costs and found greater off-farm labor participation by farm households decreases on-farm efficiency. Goodwin and Mishra concluded that their findings appeared to support Smith's (2002) contentions.

Fernandez-Cornejo and Caswell (2006) provided an examination of the first ten years of genetically engineered (GE) crops in the U.S. Noting that BES acres grew faster during the first decade than acres for GE corn or cotton, Fernandez-Cornejo and Caswell found "no significant association with net farm returns" and adoption (p. 11). Farmer expectations for higher yields from herbicide-tolerant soybeans were discovered in ARMS data from 2001 through 2003. Fernandez-Cornejo and Caswell (2006) noted the perceived BES advantages of simpler weed control requiring less management time and the particular use of time savings being applied toward off-farm employment rather than increased farm profitability. Fernandez-Cornejo, Hendricks, and Mishra (2005) found that " adoption of [herbicide-tolerant] soybeans is positively and significantly related to off-farm household income (p. 549)" but with no impact on-farm.

Fernandez-Cornejo (2007) found gains of farm households generating off-farm income using ARMS data from 1996 through 2001. Fernandez-Cornejo concluded that off-farm activities leave less time available for farm management leading to "less efficient farming (p. 16)." Fernandez-Cornejo found a significant positive impact of herbicide-tolerant soybean adoption on off-farm income, but no significant relationship between herbicide-tolerant soybean adoption and household income from farm production.

While the ARMS data used by the ERS is valuable, it does not present a balanced panel of data. Furthermore, these analyses examine on-farm income impacts rather than efficiency measurements. Although Fernandez-Cornejo (2007) used an efficiency analysis, the primary consideration was not on the analysis of BES – but rather an examination of the impacts of off-farm employment and the relationship with farm household income.

Chapter 3 - Data for On-Farm Analysis

The farms used in this study participated in the Kansas Farm Management Association (KFMA) program and had continuous data from 1993 through 2011. These farms also reported planting one or more of the four primary crops in Kansas (wheat, corn, soybeans, and sorghum) during the period and responded to a survey that included a query of their experience with biotechnology enhanced soybeans (BES) that included the year they first adopted the technology on their operations. The continuous farm financial data during this time period allowed for each farm's data to be used within their contemporary group in the analysis including a three-year period prior to the introduction of BES seed in 1996. The fifteen year horizon of the analysis beyond the year of the BES technology introduction into the market provided an opportunity to include late adopters.

A mail survey was administered in April and May of 2013 to 1,487 KFMA farms meeting the cropping criteria. Of those, 422 responses were received. For the purposes of this analysis, the key question to match with the KFMA cost, revenue, and production data was identification of the first year that the farm adopted the use of BES varieties (Funk and Bergtold, 2014). After matching survey responses to the KFMA database, 129 farms were identified as suitable for this analysis with both usable survey data and continuous KFMA financial and production data from 1993 through 2011.

3.1 Outputs

The outputs included in this analysis were production of: corn, soybeans, sorghum, wheat, and other crops. The output data were derived from the crop production for corn, soybeans, sorghum, wheat and the total gross value of crop production (TGVCP) reported for the farms in the sample in the KFMA Databank. The KFMA Databank variable TGVCP represents the dollar value of production, crop insurance proceeds, and government payments (Langemeier, 2010). USDA-NASS Quick Stats was used to obtain values for Kansas state average prices for corn, soybeans, sorghum, and wheat (USDA-NASS, 2015). Prices were multiplied by the total production for each crop to determine crop revenue for each crop type for each farm. The sum of the revenues for corn, soybean, sorghum, and wheat were then subtracted from TGVCP to provide a value of revenue for "other crops." The USDA-NASS price index for "Field Crops, Other, Including Hay – Index for price received, 2011" was used as a proxy for the price of "other crops" for the years 1993 through 2011 (USDA-NASS, 2015). Dividing the calculated "other crops" revenue by the price index provided a quantity index (i.e., output level) for each farm's "other crop" category in the analysis.

3.2 Inputs

The inputs included in this analysis were grouped into five categories: labor, general, direct inputs, maintenance, and energy. All prices were indexed using USDA-NASS Index for Prices Paid, 2011 (USDA-NASS, 2015). For each of the five grouped categories, the specific index that was used will be identified in this section. When only the index values are identified, they were used as the representative price for the category. If a reference price other than the index value for the category was used, it is cited and then the USDA-NASS index applied to derive prices for that category for all other years in the analysis.

Labor: The Labor category included the value for Hired Labor and Unpaid Family Labor. Expenditures for each farm were available for Hired Labor and Unpaid Family Labor. Prices for labor were standardized across all farms in each year using a base price from a 2008 survey of KFMA members developed by Roehl and Herbel (2009) based upon total compensation of $26,311 per year per farm laborer. This compensation level was assumed as the price for Labor in 2008. To derive the Labor price for a single year, the reference price ($26,311) was multiplied by the ratio of that year's index number from the USDA-NASS "Labor, Wage Rates – Index for Price Paid, 2011" (USDA-NASS, 2015) to the indexed number from 2008 (which was 97). Since the Index for Price Paid, 2011 is referenced to the year 2011, that index is 100. Thus, the reference price for Labor in this study for 2011 was computed as in equation (25).

(25) Labor Price assumed for 2011 = $(\$26{,}311) \times \left(\frac{100}{97}\right) = \$27{,}124.74$

The recorded expenditures for Hired Labor and Unpaid Family Labor were summed for each farm and divided by the standardized labor price for the year to develop a quantity index of labor.

General: The General category included the KFMA Data Bank information on: Feed Purchased; Organization Fees, Dues, and Publications; Crop Marketing and Storage; Crop Insurance; Conservation; General Farm Insurance; Motor Vehicle and Listed Property Depreciation; Machinery and Equipment Depreciation; and Building Depreciation. Expenditures for each farm were available for each of the general categories listed. Prices for general expenses were standardized across all farms in each year using an assumed reference price based on the first year in the analysis, 1993. The general price for a single year was equal to the ratio of that year's index number from the USDA-NASS "PITW, (Production Items, Interest Taxes & Wage Rates) – Index for Price Paid, 2011" (USDA-NASS, 2015) to the indexed number from 1993 (which was 49). Since the Index for Price Paid is referenced to the year 2011 that index is 100. Thus, the reference price for General expenses in this study for 2011 was computed as in equation (26) for that year.

(26) General Price assumed for 2011 = $\frac{100}{49} = \$2.04$

The recorded expenditures for the listed categories in General expenses were summed for each farm and divided by the standardized general price for the year to develop a quantity index of general inputs used.

Direct inputs: The variables used to calculate direct inputs include: Seed and Other Crop Expense; Fertilizer and Lime; and Herbicide and Insecticide. The 2012 reference prices for each subcategory (seed, fertilizers, herbicides, and insecticides) were developed assuming farms used the reported input levels with corresponding expenses for 133-bushel corn, 40-bushel soybeans, 100-bushel sorghum, and 60-bushel wheat in the respective expense subcategories from representative 2012 K-State Research and Extension Cost-Return Budgets (O'Brien and Duncan, 2012; Dumler and Shoup, 2012). Each year's prices for the respective subcategory (seed, fertilizer, herbicides, and insecticides) by crop were standardized across all farms in each year using the reference price in 2012. The USDA-NASS Indices applied for these expenses were from the Price Paid for: Seed & Plants Totals; Fertilizer Totals, Incl Lime & Soil Conditioners; Herbicide; and Insecticides respectively (USDA-NASS, 2015). The price for fertilizer applied to wheat in each year would be equal to the ratio of the Fertilizer Total Price Paid, 2011 Fertilizer index for that year to the indexed number from 2012 (which was 101). The overall fertilizer expense for 60-bushel wheat in O'Brien and Duncan (2012) was \$88.20. Since the Index for Price Paid, 2011 is referenced to the year 2011, that index is 100. Thus, the reference price for wheat fertilizer in 2011 in this study was computed as in equation (27).

(27) Wheat Fertilizer Price in 2011 = $(\$88.20) \times \left(\frac{100}{101}\right) = \$87.33$

In order to apply relative prices and direct crop input expenses in a manner that reflects differing prices and quantities by crop, a technique was developed to assign representative expenses levels in this study. Each farm's reported acres of corn, soybeans, sorghum and wheat individually were divided by that farm's total reported crop acres to develop a share of that farm's total Direct expenses by crop. That share by crop was multiplied to the subcategory (seed, fertilizer, herbicides, and insecticides) prices for each crop in that year. Any remaining crop acres over those assigned to corn, soybeans, sorghum, and wheat in a year for each farm were assumed to be an "other crop" acre. The share of other crop acres was multiplied to the average price for each subcategory across all four crops (corn, soybeans, sorghum, and wheat). Adding all of the prices for each subcategory across the five crops (corn, soybeans, sorghum, wheat, and other crop) we arrive at the farm's assumed price for the subcategory for that year. Since Herbicide and Insecticide are combined as one expense variable in the KFMA Databank, those were summed to obtain a single price. Thus the prices for three expense categories match the KFMA Databank information on expenditures for Seed and Other Crop Expense; Fertilizer and Lime; and Herbicide and Insecticide. To create a single price for "Direct inputs" a weighted average price across the three subcategories was created based on the contribution of each subcategory to the overall "Direct input" expense by farm. The recorded expenditures for Seed and Other Crop Expense; Fertilizer and Lime; and Herbicide and Insecticide were summed for each farm and divided by the standardized direct input price for the year to develop a quantity index of direct inputs used.

Maintenance: The maintenance used the KFMA Databank variables of Building Repairs, Irrigation Repair, Machine Hire, and Machinery Repairs. Expenditures for each farm were available for each of the maintenance categories listed. Prices for maintenance expenses were standardized across all farms in each year using an assumed reference price based on the first year in the analysis, 1993. The Maintenance price for a single year was equal to the ratio of that year's index number from the USDA-NASS "PITW, (Production Items, Interest Taxes & Wage

Rates) – Index for Price Paid, 2011” (USDA-NASS, 2015) to the indexed number from 1993 (which was 49). The recorded expenditures for the listed categories in Maintenance expenses were summed for each farm and divided by the standardized maintenance price for the year to develop a quantity index of maintenance inputs used.

Energy. The categories used to compute this input variable were: Fuel and Oil, Auto Expense, Irrigation Energy, and Utilities. Expenditures for each farm were available for each of the energy categories above. Prices for energy expenses were standardized across all farms in each year using an assumed reference price based on the first year in the analysis, 1993. The Energy price for a single year was equal to the ratio of that year’s index number from the USDA-NASS “Fuels, Diesel – Index for Price Paid, 2011” (USDA-NASS, 2015) to the indexed number from 1993 (which was 23). Since the Index for Price Paid, 2011 is referenced to the year 2011, that index is 100. Thus, the reference price for Energy expenses in this study for 2011 was computed as in equation (28).

(28) Energy Price assumed for 2011 = $\frac{100}{23} = \$4.35$

The recorded expenditures for the listed categories in Energy expenses were summed for each farm and divided by the standardized energy price for the year to develop a quantity index of energy inputs used.

3.3 Summary Statistics for a Sample of Kansas Farms

Table 3.1 contains summary statistics of the KFMA Databank information on crop acres and the total gross value of crop production providing an overview the 129 Kansas farms in the study sample. Table 3.2 contains summary statistics for output units of the 129 Kansas farms in the sample used for this study.

The average number of crop acres for the sample farms in this analysis grew from 921 in 1993 to 1249 in 2011. Soybean acres showed the largest average growth in acres in this analysis, from 179 in 1993 to 398 acres in 2011. Corn showed the second highest growth in acres – and the largest percentage growth – from 70 acres in 1993 and 277 acres in 2011. Sorghum acres were at 182 in 1993 and peaked at 207 acres on average in 1996. By the end of the analysis in 2011, average sorghum acres had decreased to 90 acres.

The average total gross value crop production recorded by farms in the sample generally grew from $138,047 in 1993 to $451,700 in 2011. With a range in 2011 from $10,142 to $2,298,878 – the total gross value crop production indicates a large difference between the total value of crops produced by farms in this sample. The maximum total gross value crop production in 1993 was $565,565 and that maximum for this sample did not exceed $1 million until 2001.

Table 3.1 Summary Statistics for a Sample of Kansas Farms

		1993	1994	1995	1996	1997	1998
Total Crop Acres Per Farm	Mean	921	975	966	991	1049	1058
	Min	196	205	194	40	85	85
	Max	2582	3952	2358	2416	2416	3353
	Std Dev	509	580	518	538	554	590
Soybean Acres	Mean	179	209	221	215	260	260
	Min	0	0	0	0	0	0
	Max	1393	1419	1606	1429	1715	1513
	Std Dev	254	274	297	273	329	307
Corn Acres	Mean	70	98	76	109	120	120
	Min	0	0	0	0	0	0
	Max	682	871	830	1035	1183	926
	Std Dev	133	166	157	199	219	195
Sorghum Acres	Mean	182	182	177	207	198	193
	Min	0	0	0	0	0	0
	Max	876	995	909	976	983	1135
	Std Dev	164	171	166	193	198	194
Wheat Acres	Mean	324	326	330	327	325	335
	Min	0	0	0	0	0	0
	Max	1297	1330	1333	1394	1310	1311
	Std Dev	303	327	326	324	340	334
Total Gross Value Crop	Mean	138047	164480	153110	214476	218322	171585
Production	Min	19889	28037	23394	9357	12525	10540
(Dollars)	Max	565565	593314	676814	901991	838124	666111
	Std Dev	98407	113102	109620	160992	142677	122507

Table 3.1 Summary Statistics for a Sample of Kansas Farms (continued)

		1999	2000	2001	2002	2003	2004
Total Crop Acres Per Farm	Mean	1035	1047	1085	1098	1143	1140
	Min	76	89	85	134	134	134
	Max	2583	2603	3740	2831	2828	4240
	Std Dev	559	584	639	631	667	715
Soybean Acres	Mean	276	274	295	276	267	267
	Min	0	0	0	0	0	0
	Max	1592	1584	2516	1930	1391	1152
	Std Dev	324	309	351	314	301	281
Corn Acres	Mean	123	141	161	162	159	168
	Min	0	0	0	0	0	0
	Max	1129	950	1208	996	1091	942
	Std Dev	210	209	238	233	234	225
Sorghum Acres	Mean	175	174	167	164	181	158
	Min	0	0	0	0	0	0
	Max	830	777	582	692	1236	1048
	Std Dev	179	172	161	184	220	200
Wheat Acres	Mean	272	315	306	343	360	372
	Min	0	0	0	0	0	0
	Max	1379	1407	1415	2399	2220	2480
	Std Dev	329	354	328	408	381	427
Total Gross Value Crop	Mean	169897	178160	189022	175388	213429	224961
Production	Min	10780	15275	11142	12881	16355	16611
(Dollars)	Max	832740	652866	1209665	751727	1004554	740702
	Std Dev	129199	130497	149435	128522	160029	159904

Table 3.1 Summary Statistics for a Sample of Kansas Farms (continued)

		2005	2006	2007	2008	2009	2010	2011
Total Crop Acres Per Farm	Mean	1168	1161	1198	1224	1245	1247	1249
	Min	115	109	86	85	54	90	90
	Max	4240	3236	4371	4410	4515	3917	4245
	Std Dev	739	710	818	824	816	790	817
Soybean Acres	Mean	293	327	290	337	378	427	398
	Min	0	0	0	0	0	0	0
	Max	1668	1541	1550	1690	1828	2482	2032
	Std Dev	317	334	308	351	406	413	394
Corn Acres	Mean	206	203	216	212	221	263	277
	Min	0	0	0	0	0	0	0
	Max	1306	1355	1529	1123	1164	1288	1521
	Std Dev	279	284	307	272	270	299	332
Sorghum Acres	Mean	147	115	126	119	107	94	90
	Min	0	0	0	0	0	0	0
	Max	744	749	1354	1199	785	794	708
	Std Dev	185	171	219	193	168	162	159
Wheat Acres	Mean	352	357	422	410	361	284	339
	Min	0	0	0	0	0	0	0
	Max	2371	2464	2857	2866	2855	2547	2131
	Std Dev	437	419	491	475	444	424	419
Total Gross Value Crop	Mean	227565	255860	356946	428340	422820	447877	451700
Production	Min	14808	11739	1595	7774	13571	30772	10142
(Dollars)	Max	975995	1079186	1543201	2117129	1825755	1735879	2298878
	Std Dev	171006	201661	306919	367427	351026	365632	413061

Table 3.2 Summary Statistics of Outputs for a Sample of Kansas Farms

Output Units		1993	1994	1995	1996	1997	1998
Corn (Bushels)	Mean	6295	10346	7495	14660	13642	15104
	Min	0	0	0	0	0	0
	Max	107992	143702	120307	176589	161641	157405
	Std Dev	15611	21502	18729	32585	27673	30224
Soybeans (Bushels)	Mean	4706	7823	5591	7843	9631	7232
	Min	0	0	0	0	0	0
	Max	34727	75655	66220	57637	87470	54316
	Std Dev	6973	12447	9203	10713	13016	9878
Sorghum (Bushels)	Mean	11560	14995	10780	16970	16990	14474
	Min	0	0	0	0	0	0
	Max	55694	65718	58507	74751	89375	73666
	Std Dev	11940	14804	11136	15715	17734	15243
Wheat (Bushels)	Mean	9354	13070	8112	10245	16383	15359
	Min	0	0	0	0	0	0
	Max	55920	58441	37887	60501	98259	72205
	Std Dev	11280	13687	8478	11687	18411	16872
Other Crops	Mean	465	318	275	389	427	537
(Calculated Units)	Min	0	0	0	0	0	0
	Max	1956	1456	1323	2026	1916	2164
	Std Dev	342	289	279	362	334	345

Table 3.2 Summary Statistics of Outputs for a Sample of Kansas Farms (continued)

Output Units		1999	2000	2001	2002	2003	2004
Corn (Bushels)	Mean	13037	16520	18404	13669	14779	25924
	Min	0	0	0	0	0	0
	Max	186974	157814	184880	170601	177002	187963
	Std Dev	27931	29898	34306	26978	28213	38535
Soybeans (Bushels)	Mean	7723	4431	9293	5926	5825	10706
	Min	0	0	0	0	0	0
	Max	66431	55140	92882	41757	47510	65436
	Std Dev	10449	7180	13016	8077	8012	12677
Sorghum (Bushels)	Mean	13664	12065	11214	9215	8302	15265
	Min	0	0	0	0	0	0
	Max	67375	70647	57120	52572	61852	143160
	Std Dev	14980	14150	12041	11732	11117	22079
Wheat (Bushels)	Mean	12309	12809	13397	13179	19258	15361
	Min	0	0	0	0	0	0
	Max	74725	82740	64430	85287	111851	94088
	Std Dev	15530	15491	14797	15695	22452	16952
Other Crops	Mean	777	830	672	485	598	443
(Calculated Units)	Min	0	27	0	0	0	0
	Max	8840	4632	3533	3619	2111	2139
	Std Dev	864	675	548	451	465	404

Table 3.2 Summary Statistics of Outputs for a Sample of Kansas Farms (continued)

Output Units		2005	2006	2007	2008	2009	2010	2011
Corn (Bushels)	Mean	23590	20179	26846	26667	30265	29012	19090
	Min	0	0	0	0	0	0	0
	Max	227312	173316	252161	183062	249198	232968	219201
	Std Dev	38849	34480	44058	38630	43417	39796	36430
Soybeans (Bushels)	Mean	10553	9488	8779	12419	16163	13508	9092
	Min	0	0	0	0	0	0	0
	Max	66950	68407	63456	69153	83336	74290	73272
	Std Dev	12348	10932	11281	13841	17800	13853	11478
Sorghum (Bushels)	Mean	10951	7361	10375	10868	10542	7749	5150
	Min	0	0	0	0	0	0	0
	Max	65355	75245	116416	125178	91557	83694	72669
	Std Dev	14712	12866	18567	19722	18260	14658	11725
Wheat (Bushels)	Mean	14497	14181	8604	16883	15754	11572	13509
	Min	0	0	0	0	0	0	0
	Max	105410	108845	77514	112380	115832	92865	111150
	Std Dev	20106	17682	11323	22266	20835	18177	17547
Other Crops	Mean	641	514	777	586	619	740	962
(Calculated Units)	Min	0	0	0	0	0	0	0
	Max	2789	4343	7454	5008	3594	7276	5413
	Std Dev	532	598	1123	708	613	990	1108

Table 3.3 contains summary statistics for input category expenses of the KFMA Databank information for the 129 Kansas farms in the sample. Figure 3.1 displays the means for each of the five input category expenses in the sample periods.

The largest nominal and percentage growth expense was for direct inputs. This expense category grew from an average for the sample farms of $27,670 in 1993 to $130,017 in 2011. The average for each of the final four years in the analysis was in excess of $100,000. With direct inputs including expenses for seed and fertilizer, the growth in the average number of corn acres in the sample farms would likely lead to an increase in this expense category.

General farm expenses grew from a mean of $41,953 in 1993 to $92,573 in 2011. Average maintenance expenses for the sample farms were at their lowest in 1993 at $20,371 and peaked for the analysis in 2010 at $40,260. The highest average energy expenses recorded was in 2008 at $34,093. The general expense category was the largest for the farms on average in the early periods of this study. By the end of the study, general farm expense was the second highest expense category.

Maintenance expenses were the third highest expense input category on average. Rising from $20,371 on average in 1993 to exceed $40,000 on average per year for the sample farms in 2010 and 2011, this expense category nearly doubled.

The energy expense category was consistently the second lowest on average for the inputs considered in this study. Having reached a highest average across all the sample years in 2008 of $34,093, energy had increased over two-times from the lowest average in 1995 of $11,562. Energy expenses can make a significant difference on farm financial performance and inter-year differences in expenses can be dramatic (Dhuyvetter et al., 2005).

Labor expenses, on average in the sample periods, ranged from $8,272 in 1993, and reached the highest mean for the sample farms of $13,488 in 2010. The minimum expenses recorded for labor are $0 in each year. Some farms do not charge (recognize) labor in the financial performance of the farm. The maximum labor expenses recorded range from $84,323 in 2003 to $231,632 in 2011. Labor was the lowest input expense category on average in each of the sample periods in this study. If all farms accounted for labor, we would expect their individual efficiency scores to potentially reduce – or possibly remain constant if they were fully-efficient.

Figure 3.2 shows the number of farms with BES adoption experience cumulatively from 1996 through 2011. Although data was used from 1993 through 1995, BES technology was not commercially available during this period. Thus, the number of farms adopting BES was zero during those years. A majority of the farms in the study sample adopted BES by 2000. However, there were 36 farms who had not adopted BES by 2011 – the final period in this study.

Table 3.3 Summary Statistics of Input Expenses for a Sample of Kansas Farms

Expenses (in Dollars)		1993	1994	1995	1996	1997	1998
Labor	Mean	8272	9829	9100	9130	11004	10202
	Min	0	0	0	0	0	0
	Max	93460	112657	86837	95358	123909	120343
	Std Dev	14200	17561	13685	14015	17141	16263
General	Mean	41953	45808	47716	50447	47791	45712
	Min	6652	5119	5926	1831	8634	8006
	Max	300399	377875	382970	432886	271364	197996
	Std Dev	46012	51930	54700	61233	47092	37425
Direct Inputs	Mean	27670	32256	34677	39774	44392	42508
	Min	1427	2009	2870	3594	5430	2185
	Max	146953	156496	176862	254667	252350	200907
	Std Dev	22086	26108	28823	35656	37785	34460
Maintenance	Mean	20371	20480	20873	22421	24506	24182
	Min	668	4095	3643	1160	4384	1143
	Max	83671	77122	212374	73574	98983	84491
	Std Dev	13822	13186	21772	15615	15757	16168
Energy	Mean	12460	12383	11562	12563	13334	11685
	Min	3243	2317	2954	2699	1870	2154
	Max	55226	75353	48300	61544	79596	81118
	Std Dev	8394	9617	7388	8917	10556	10344

Table 3.3 Summary Statistics of Input Expenses for a Sample of Kansas Farms (continued)

Expenses (in Dollars)		1999	2000	2001	2002	2003	2004
Labor	Mean	10552	10655	9896	10051	8414	10149
	Min	0	0	0	0	0	0
	Max	139539	145014	168786	200903	84323	175774
	Std Dev	19298	20128	20230	21902	14704	21172
General	Mean	45625	47432	46489	51528	53128	60315
	Min	6243	7013	5499	5738	5443	3645
	Max	259561	422731	334960	381301	367974	547287
	Std Dev	42682	49976	44722	52989	55186	75573
Direct Inputs	Mean	43847	44353	51312	47233	53922	56075
	Min	2764	4342	1843	2596	3662	3870
	Max	240471	202110	341700	227055	267065	284687
	Std Dev	38992	36606	44892	40705	45240	45083
Maintenance	Mean	22921	22633	24747	23882	23669	26059
	Min	1692	1352	4046	1605	2318	511
	Max	74391	95775	109089	118938	97750	113495
	Std Dev	14452	15446	18343	18952	17529	19556
Energy	Mean	12256	15017	15593	14044	15678	18391
	Min	3546	2395	2237	2493	2222	2174
	Max	95921	109104	118111	120696	97923	104727
	Std Dev	10808	14591	14768	13847	13793	16483

Table 3.3 Summary Statistics of Input Expenses for a Sample of Kansas Farms (continued)

Expenses (in Dollars)		2005	2006	2007	2008	2009	2010	2011
Labor	Mean	10804	11010	12210	13223	12794	13488	13369
	Min	0	0	0	0	0	0	0
	Max	200682	178509	198684	198684	202460	208256	231632
	Std Dev	23483	22337	25193	26031	26293	26975	28419
General	Mean	56174	59161	63568	75488	76627	80166	92573
	Min	5917	4386	5220	2019	4741	6595	7348
	Max	417868	399561	473999	538570	529203	860757	788026
	Std Dev	59334	62422	69133	81763	77926	93206	98137
Direct Inputs	Mean	68862	69901	81979	110370	103193	110964	130017
	Min	2863	3551	2370	741	678	3165	841
	Max	368568	445749	377489	555912	500475	609047	621463
	Std Dev	59520	65996	72569	95340	98368	100028	117039
Maintenance	Mean	28107	27440	29784	36247	39585	40260	40129
	Min	1116	1412	2889	933	1003	659	1522
	Max	90272	142628	119292	248287	222752	185033	220409
	Std Dev	19186	19301	20615	30161	32199	29567	31398
Energy	Mean	22658	25055	26186	34093	23788	27929	33303
	Min	3823	3467	3419	1027	1759	4400	3183
	Max	130001	125668	178339	208553	158870	140012	161637
	Std Dev	18592	19682	24049	28962	19714	23012	27225

Figure 3.1 Average Annual Expenses for Analysis Input Categories

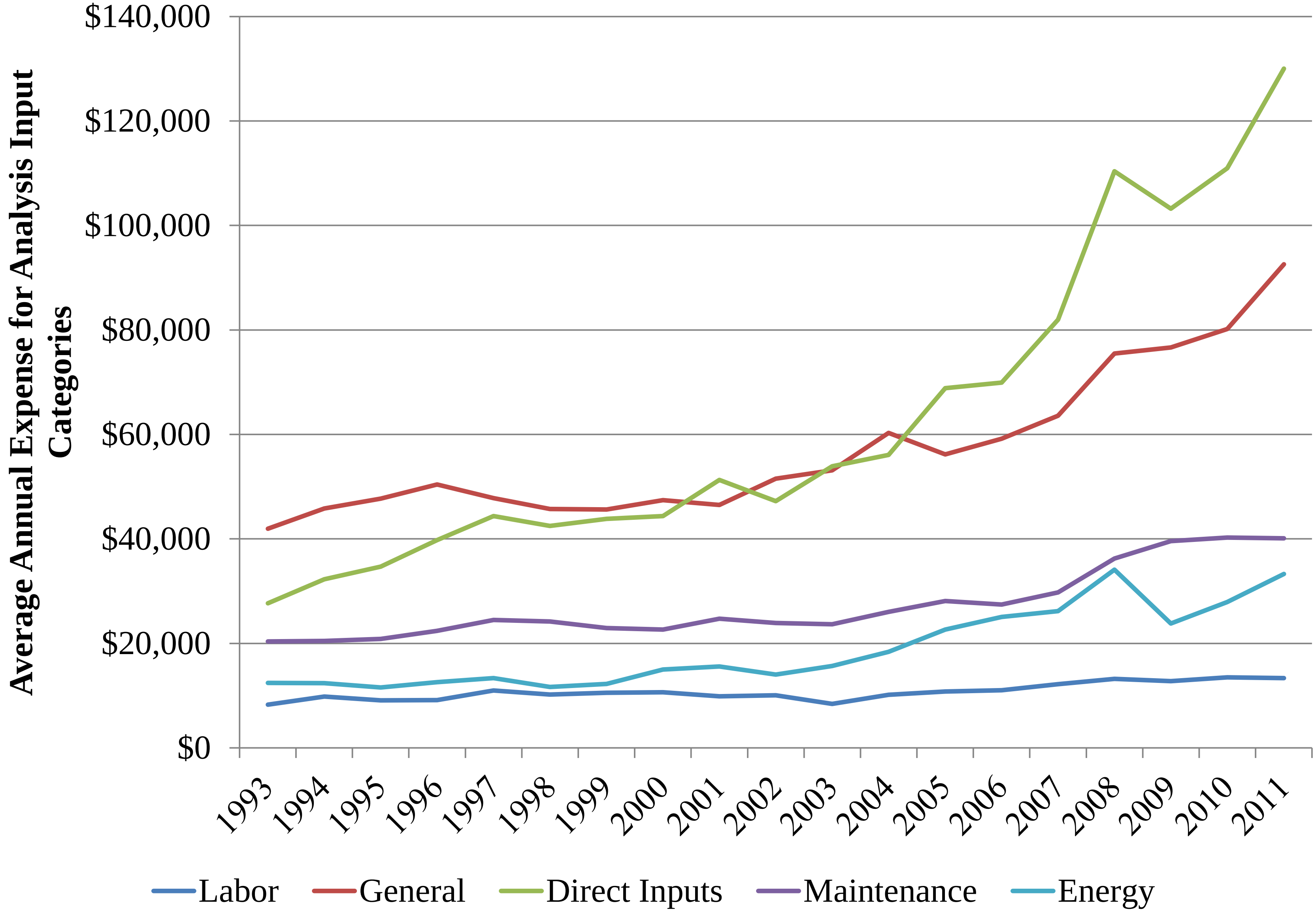
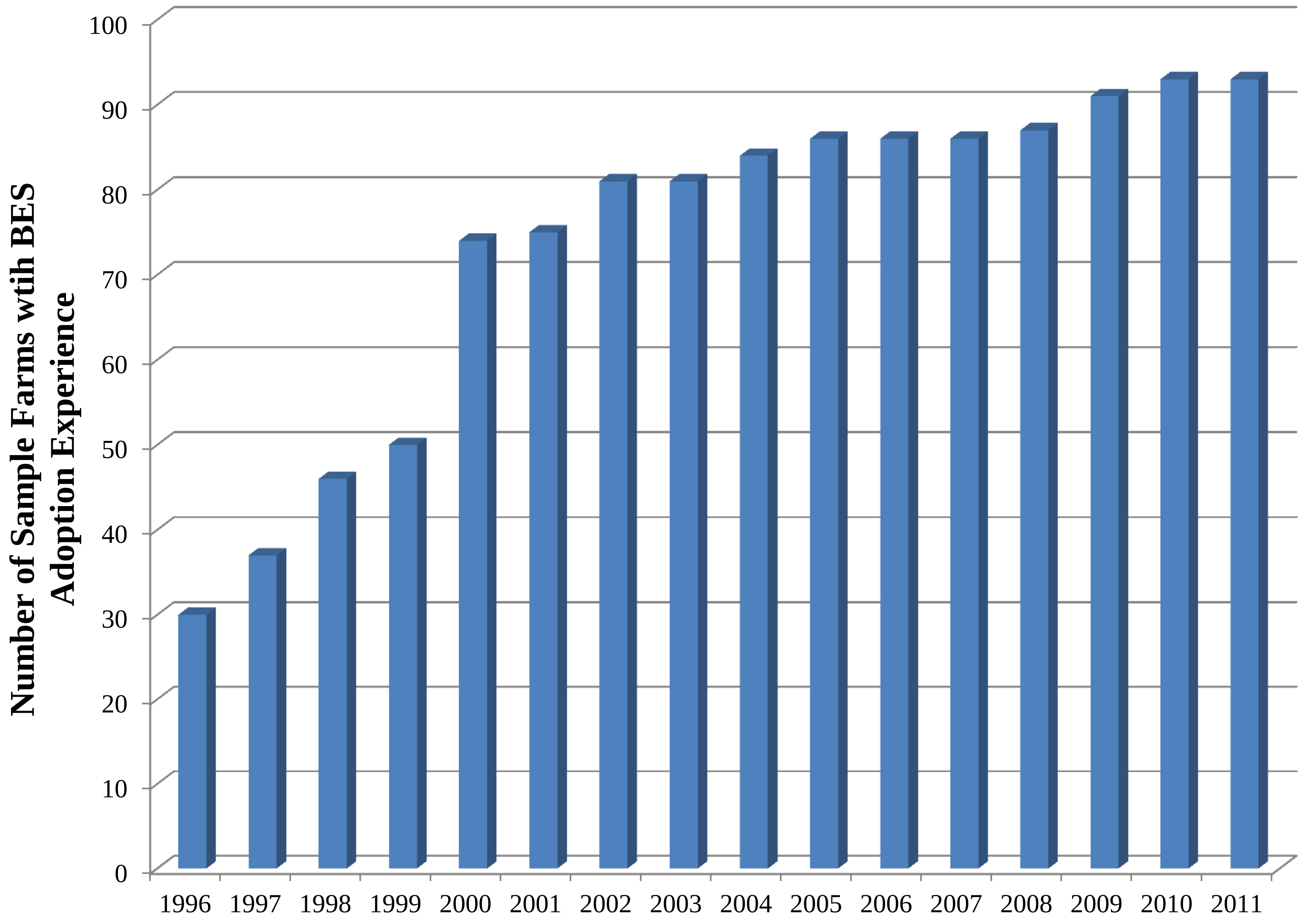


Figure 3.2 Cumulative Number of Sample Farms with BES Adoption Experience from 1996 through 2011



Chapter 4 - Technical Efficiency and BES Experience

Technical efficiency (TE) is measured assuming constant returns-to-scale (CRS) and variable returns-to-scale (VRS) and are summarized for the sample farms. The data envelopment analysis models represented by Equations (1) and (2) from section 2.2.1 were estimated for each of the sample farms for each year of the analysis using GAMS to arrive at the TE_{CRS} (overall efficiency) and TE_{VRS} (pure technical efficiency) respectively.

Results of the examination of the impacts of the adoption of BES on technical efficiency across the farms is conducted following the regression model in section 2.2.2. This regression analysis was performed in STATA. The coefficient estimate on ADOPT, β_1, is analyzed to examine the impact of the adoption of BES on TE_{VRS}.

4.1 Technical Efficiency – Constant Returns to Scale

The summary results of the TE_{CRS} measurements estimated for the sample farms in each year in the analysis are presented in Table 4.1. There are two years (1997 and 1998) in which more than fifty-percent of the farms in the sample are considered fully technically efficient under CRS – i.e., when $TE_{CRS} = 1$. The distribution of TE_{CRS} measurements for the farms 1997 and 1998 are displayed in Figure 4.1 and Figure 4.2 respectively. The highest mean TE_{CRS} of 0.89 was found in 2006. The distribution of the TE_{CRS} measurements for the farms in 2006 is displayed in Figure 4.3. Average TE_{CRS} scores for the sample population of 0.88 and 0.87 are recorded in 1997 and 1998 for the second and third highest years. The lowest mean TE_{CRS} was found in 2007 when the sample farms average is 0.74. The distribution of TE_{CRS} measurements for the farms in 2007 is displayed in Figure 4.4. The distributions of TE_{CRS} measurements for the farms in 2006 and 2007 are graphed in Figure 4.5 to display the differences between the years with the highest and lowest mean technical efficiency measures under CRS.

Table 4.1 Technical Efficiency Measures under CRS for a Sample of Kansas Farms

Summary Statistics		1993	1994	1995	1996	1997	1998
TE - CRS	Mean	0.77	0.84	0.85	0.84	0.88	0.87
	Min	0.13	0.38	0.25	0.27	0.30	0.30
	Max	1.00	1.00	1.00	1.00	1.00	1.00
	Std Dev	0.24	0.18	0.20	0.18	0.17	0.18
Distribution of Farms:							
TE-CRS < 0.40		11	1	6	3	4	1
0.40≤ TE-CRS < 0.50		10	5	3	5	3	6
0.50≤ TE-CRS < 0.60		15	7	12	7	6	9
0.60≤ TE-CRS < 0.70		13	20	9	14	7	6
0.70≤ TE-CRS < 0.80		15	17	14	16	11	14
0.80≤ TE-CRS < 0.90		5	13	12	18	17	14
0.90≤ TE-CRS < 1.00		11	12	12	13	15	9
TE-CRS = 1.00		49	54	61	53	66	70

Summary Statistics		1999	2000	2001	2002	2003	2004
TE - CRS	Mean	0.80	0.78	0.86	0.79	0.83	0.82
	Min	0.22	0.26	0.43	0.25	0.37	0.33
	Max	1.00	1.00	1.00	1.00	1.00	1.00
	Std Dev	0.22	0.22	0.16	0.21	0.19	0.18
Distribution of Farms:							
TE-CRS < 0.40		9	7	0	7	4	2
0.40≤ TE-CRS < 0.50		4	7	5	6	3	6
0.50≤ TE-CRS < 0.60		12	18	8	9	15	14
0.60≤ TE-CRS < 0.70		19	16	9	21	13	12
0.70≤ TE-CRS < 0.80		14	17	21	16	13	16
0.80≤ TE-CRS < 0.90		13	9	18	18	14	16
0.90≤ TE-CRS < 1.00		12	14	19	13	15	25
TE-CRS = 1.00		46	41	49	39	52	38

Table 4.1 Technical Efficiency Measures under CRS for a Sample of Kansas Farms (continued)

Summary Statistics		2005	2006	2007	2008	2009	2010	2011
TE - CRS	Mean	0.82	0.89	0.74	0.85	0.85	0.78	0.83
	Min	0.28	0.33	0.04	0.29	0.32	0.30	0.27
	Max	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Std Dev	0.19	0.16	0.24	0.18	0.18	0.21	0.21
Distribution of Farms:								
TE-CRS < 0.40		3	1	16	2	2	4	6
0.40≤ TE-CRS < 0.50		7	3	9	6	7	9	7
0.50≤ TE-CRS < 0.60		12	7	12	11	6	17	9
0.60≤ TE-CRS < 0.70		13	8	20	7	9	17	12
0.70≤ TE-CRS < 0.80		15	12	13	17	21	20	11
0.80≤ TE-CRS < 0.90		20	14	12	19	20	13	13
0.90≤ TE-CRS < 1.00		15	22	8	13	13	5	16
TE-CRS = 1.00		44	62	39	54	51	44	55

Figure 4.1 Cumulative Distribution Function of Technical Efficiency Measures under CRS in 1997 for a Sample of Kansas Farms

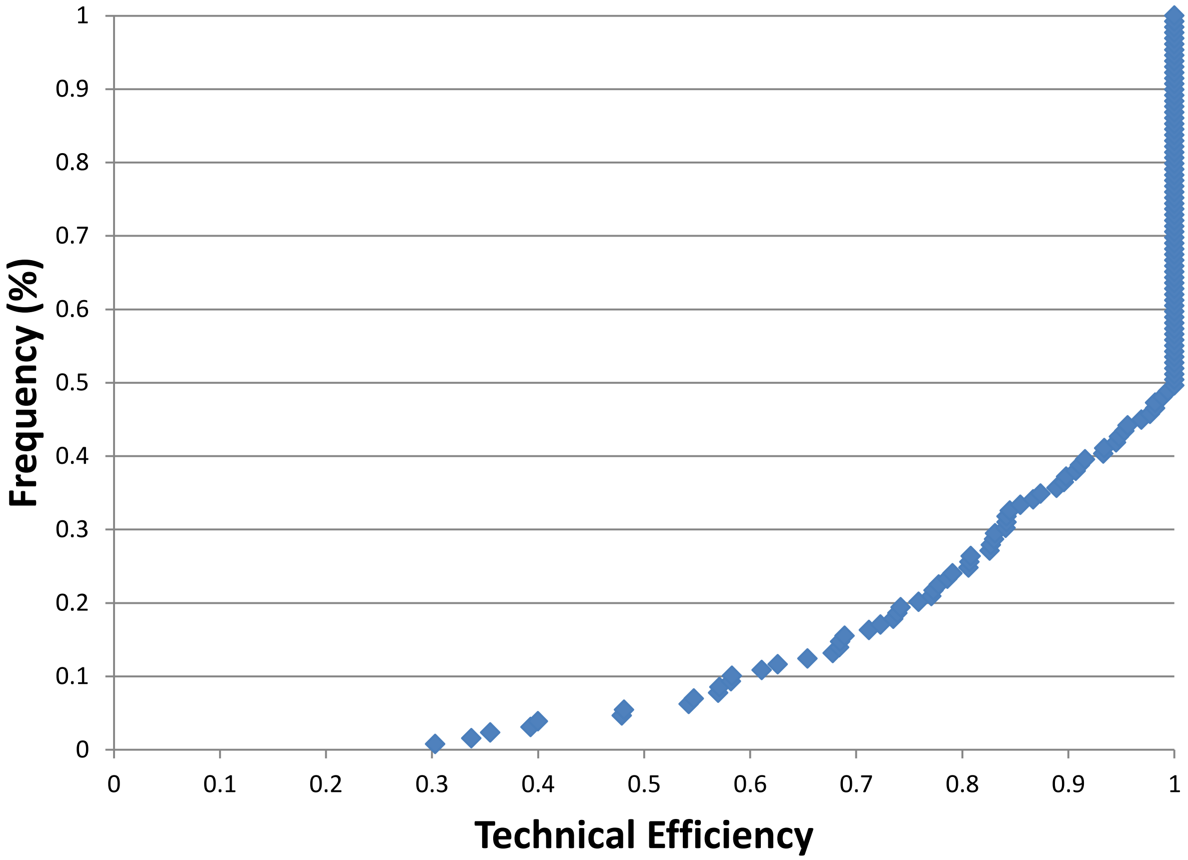


Figure 4.2 Cumulative Distribution Function of Technical Efficiency Measures under CRS in 1998 for a Sample of Kansas Farms

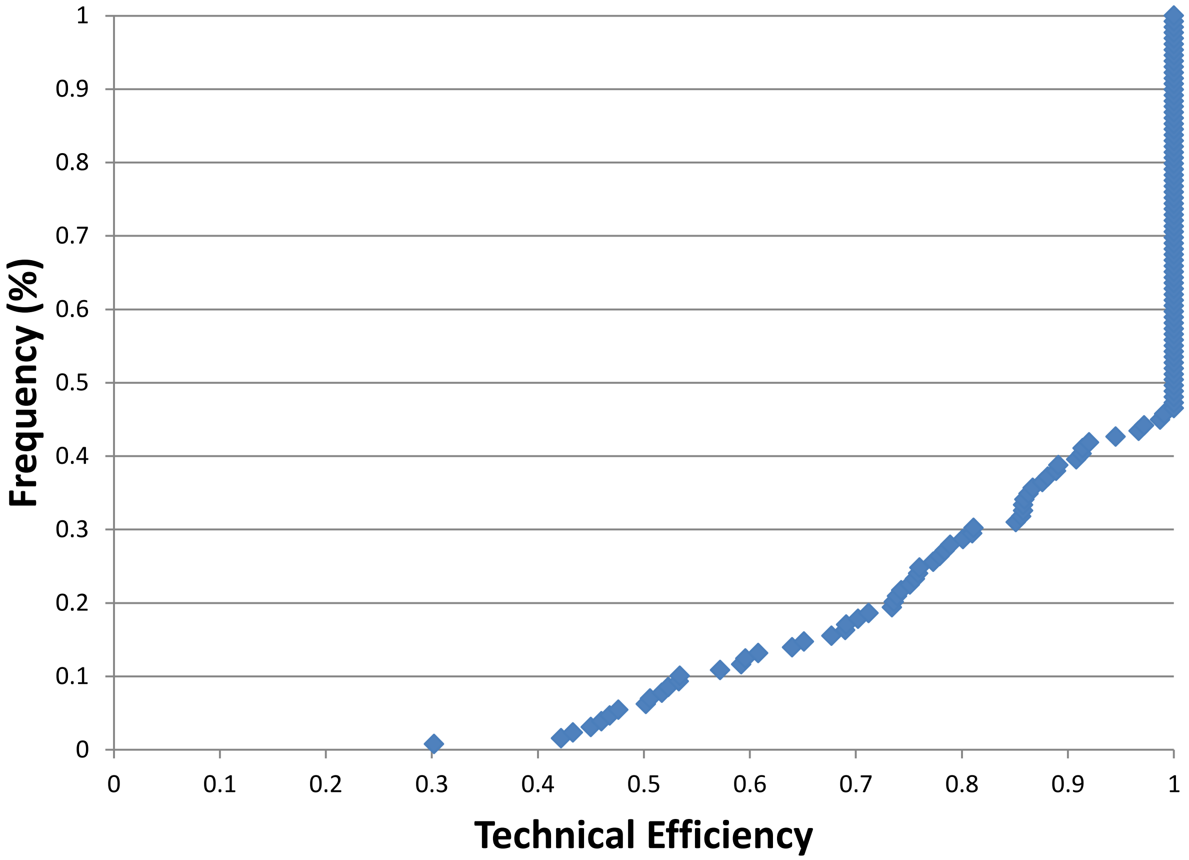


Figure 4.3 Cumulative Distribution Function of Technical Efficiency Measures under CRS in 2006 for a Sample of Kansas Farms

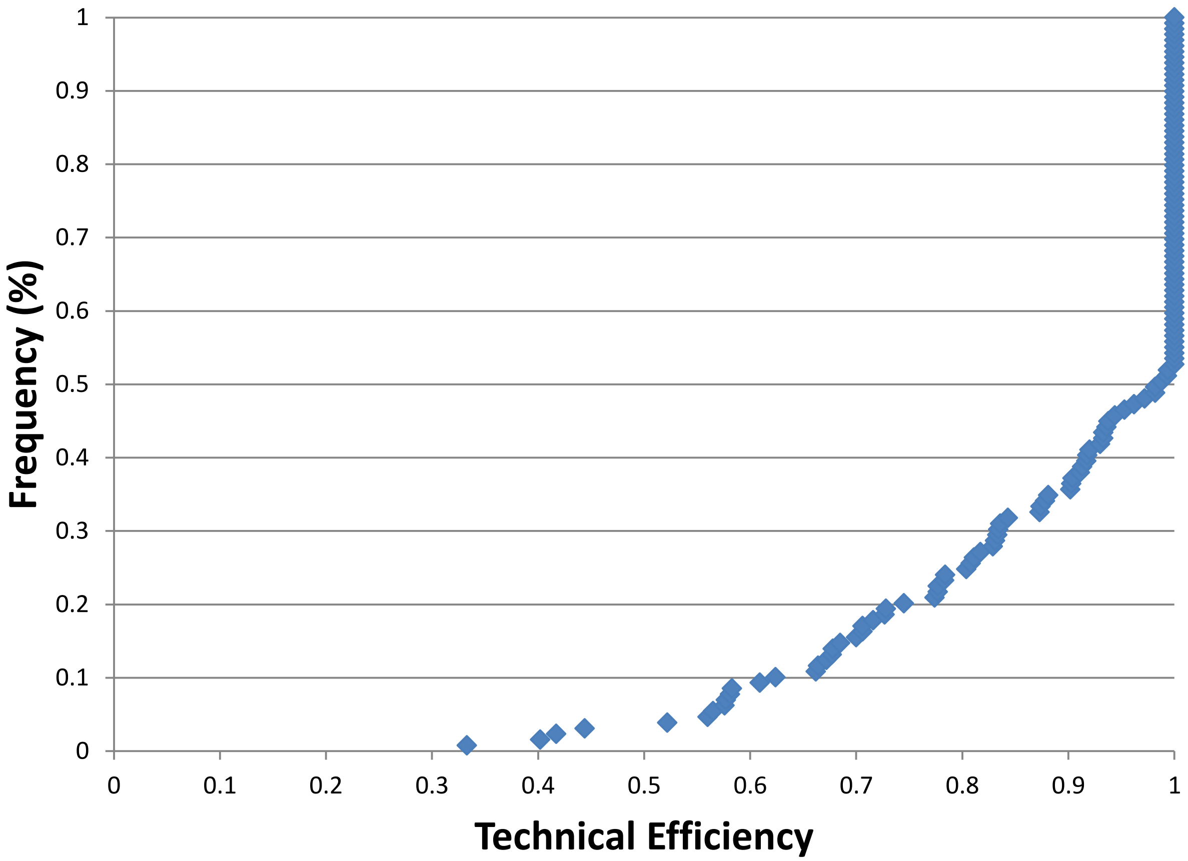


Figure 4.4 Cumulative Distribution Function of Technical Efficiency Measures under CRS in 2007 for a Sample of Kansas Farms

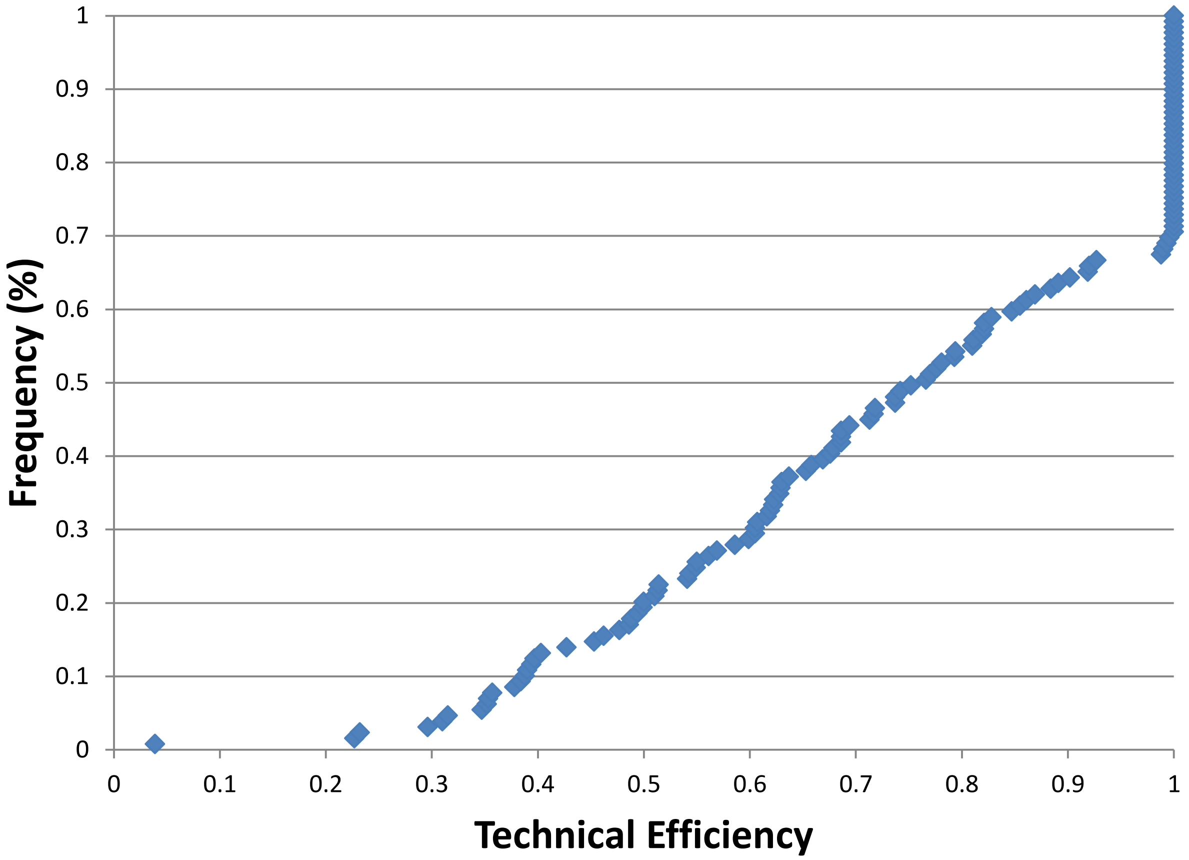
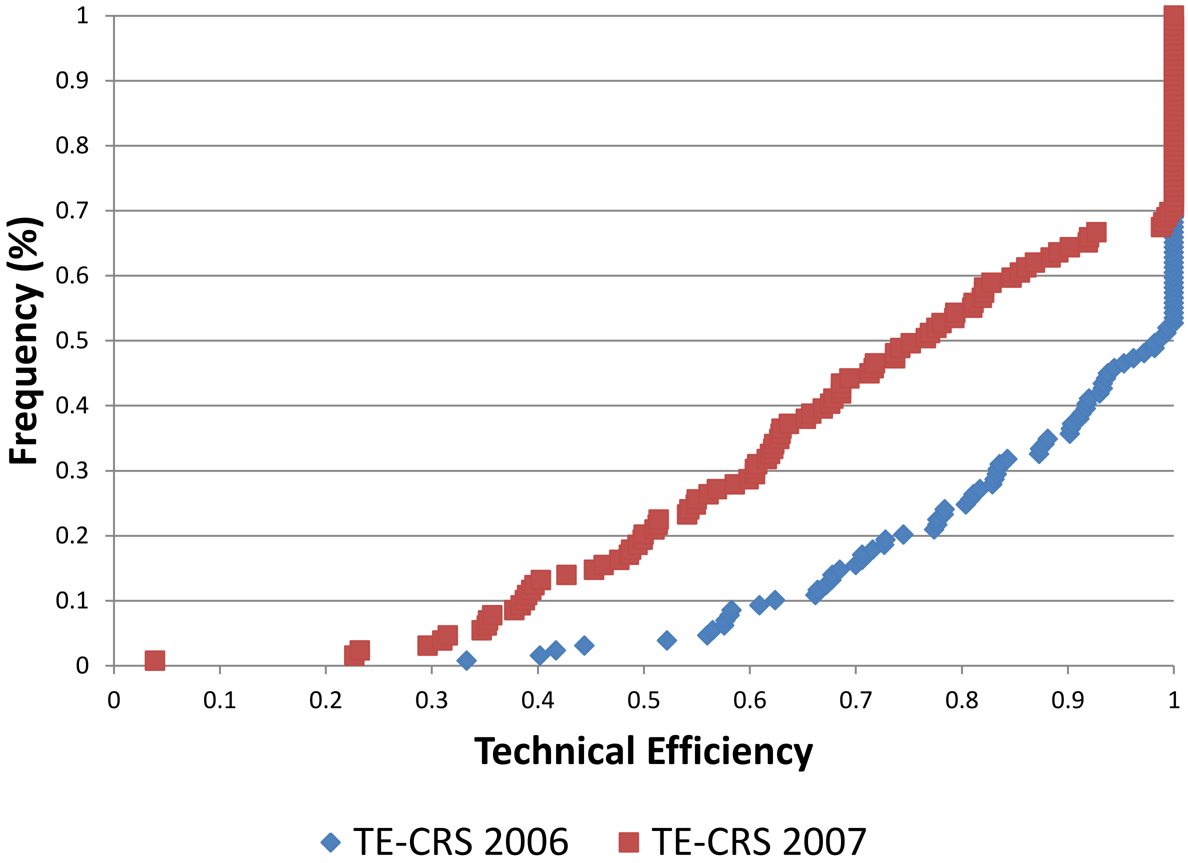


Figure 4.5 Cumulative Distribution Functions of Technical Efficiency Measures under CRS in 2006 and 2007 for a Sample of Kansas Farms



4.2 Technical Efficiency – Variable Returns to Scale

The summary results of the TE_{VRS} measurements estimated for the sample farms in each year are presented in Table 4.2. There are fourteen years out of nineteen in which fifty-percent or more of the farms in the sample are technically efficient under VRS – i.e., when $TE_{VRS} = 1$. The highest mean TE_{VRS} across the sample of farms was 0.93 that occurred in 1997. Figure 4.6 displays the distribution of the TE_{VRS} measurements for the farms in 1997. The second highest mean TE_{VRS} was 0.92 in 1998 and 2006. The years with the highest mean TE_{VRS} values are not unexpected given the summary results of the TE_{CRS}. The lowest mean TE_{VRS} of 0.81 was found in 2007, the same when examining the summary of the TE measurements under CRS. The distribution of the TE_{VRS} measurements for the farms in 2007 is shown in Figure 4.7. Figure 4.10 displays the distributions of TE_{CRS} and TE_{VRS} for 2007 in the same graph where it can be seen that the distribution for the years with lowest mean TE_{VRS} estimated is at a higher level than the distribution found under CRS. The average standard deviation in the sample across the years was lower for TE_{VRS} than for TE_{CRS}, 0.17 and 0.19 respectively (Table 4.2). The number of fully efficient farms was expected to be higher under VRS than under CRS due to the nature of the tighter envelopment of data observations with the addition of the convexity constraints under VRS (Coelli et al., 2005). Comparing the distributions for technical efficiency scores under CRS and VRS for 1997 (Figure 4.9) and for 2007 (Figure 4.10) we see that VRS is at least as great as that for CRS.

Figure 4.6 Cumulative Distribution Function of Technical Efficiency Measures under VRS in 1997 for a Sample of Kansas Farms

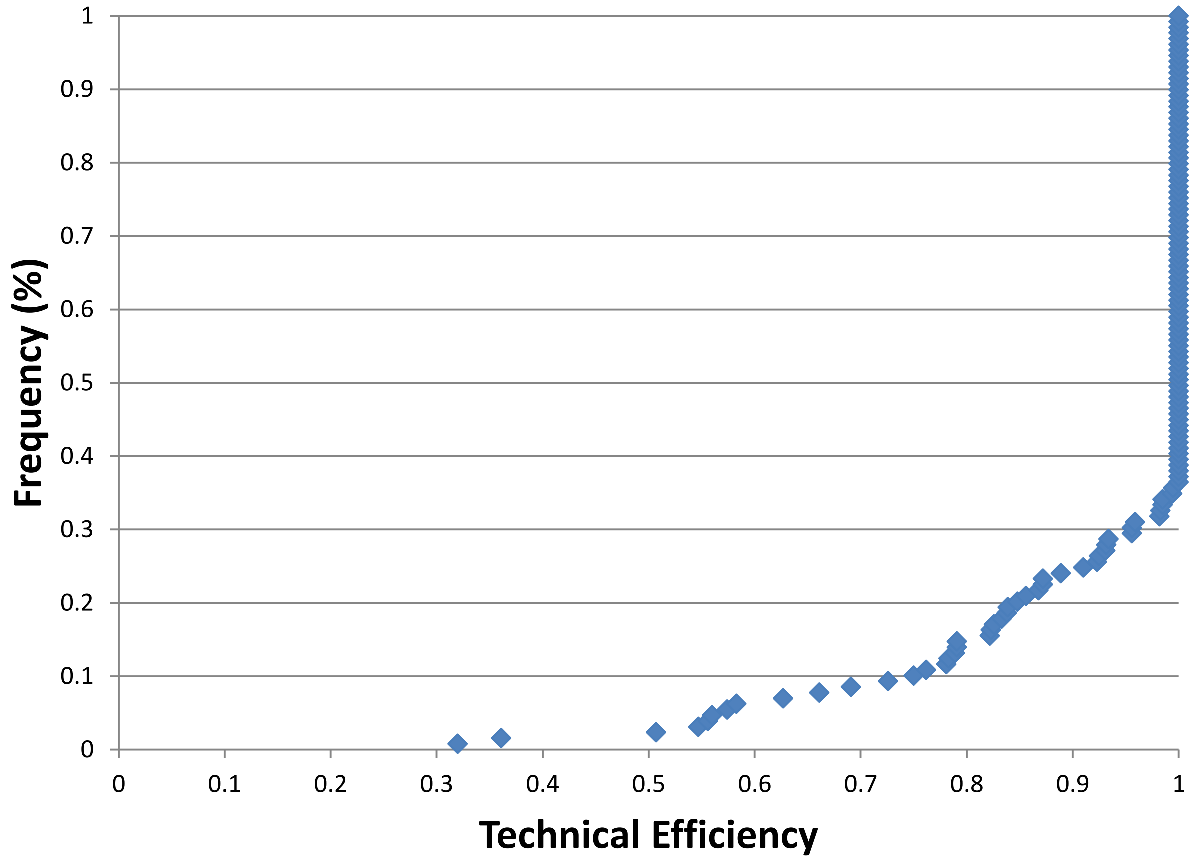


Figure 4.7 Cumulative Distribution Function of Technical Efficiency Measures under VRS in 2007 for a Sample of Kansas Farms

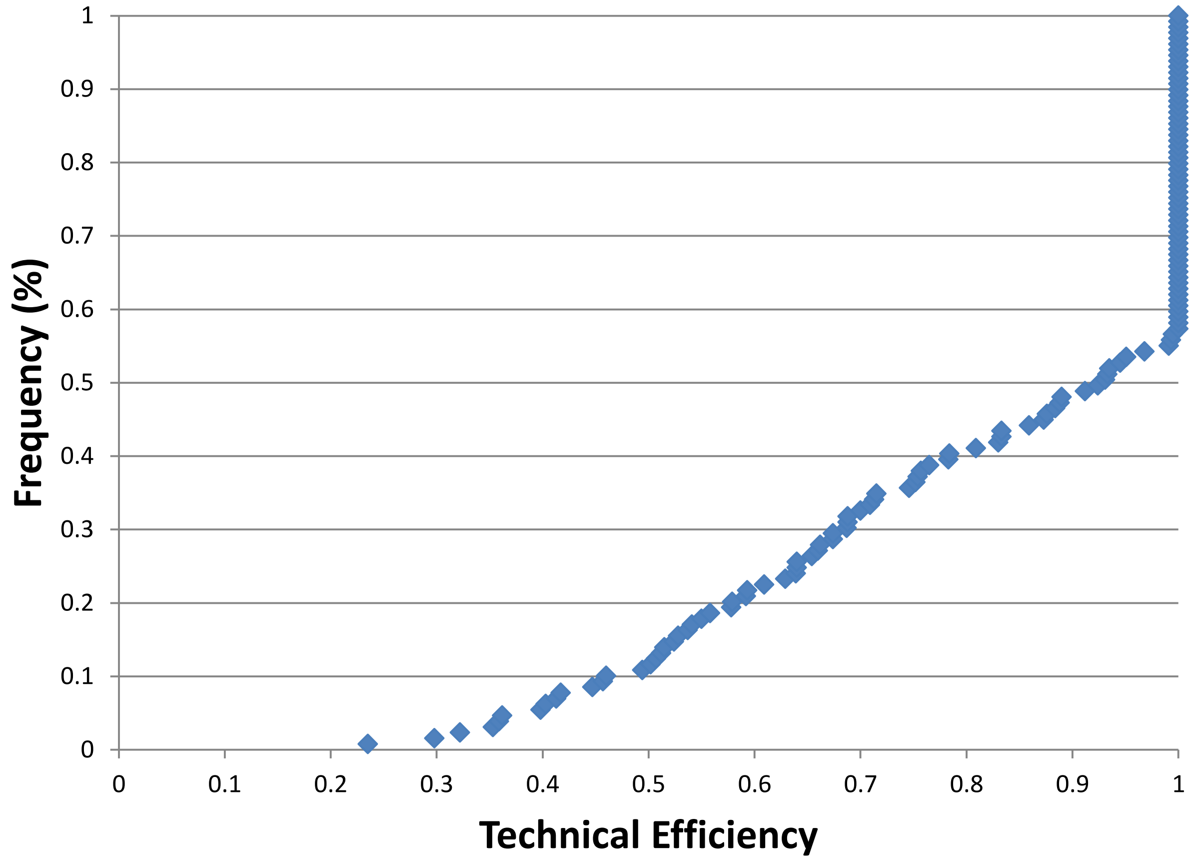


Figure 4.8 Cumulative Distribution Functions of Technical Efficiency Measures under CRS and VRS in 1997 for a Sample of Kansas Farms

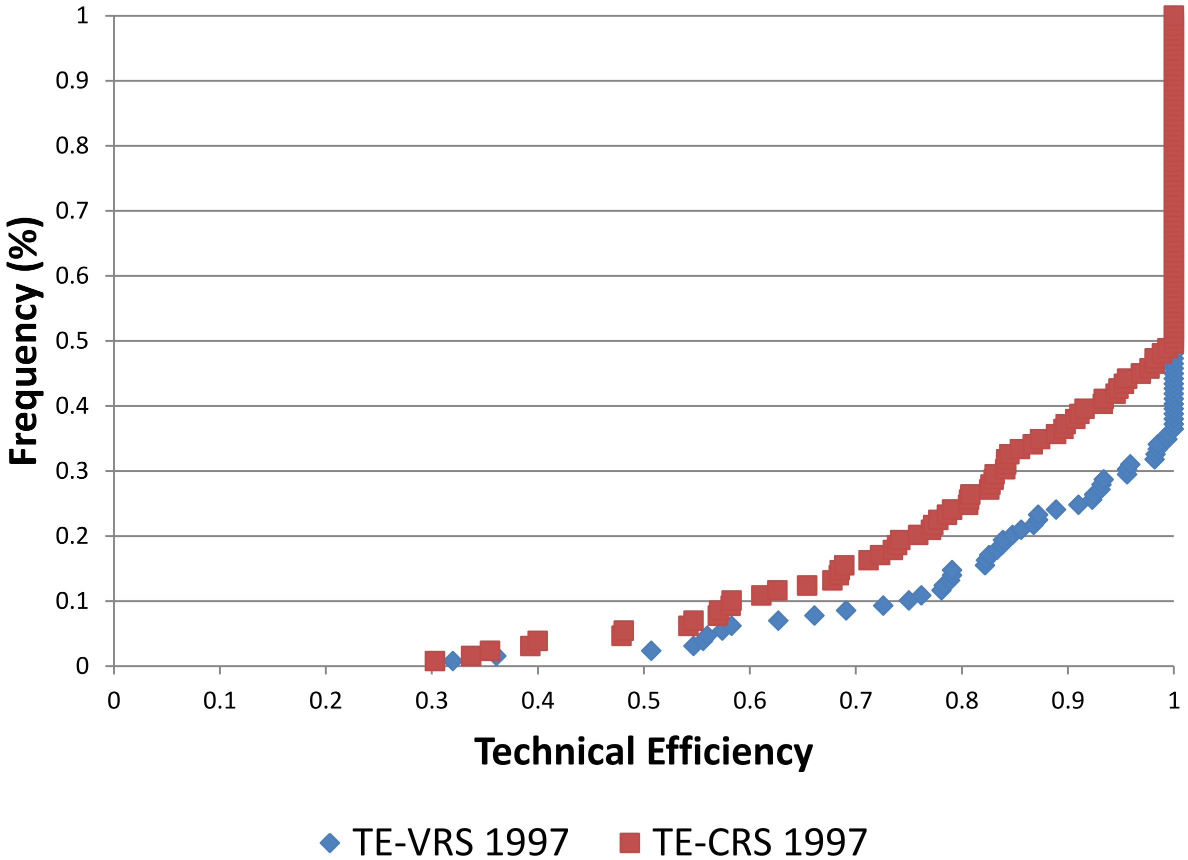


Figure 4.9 Cumulative Distribution Functions of Technical Efficiency Scores under CRS and VRS in 2007 for a Sample of Kansas Farms

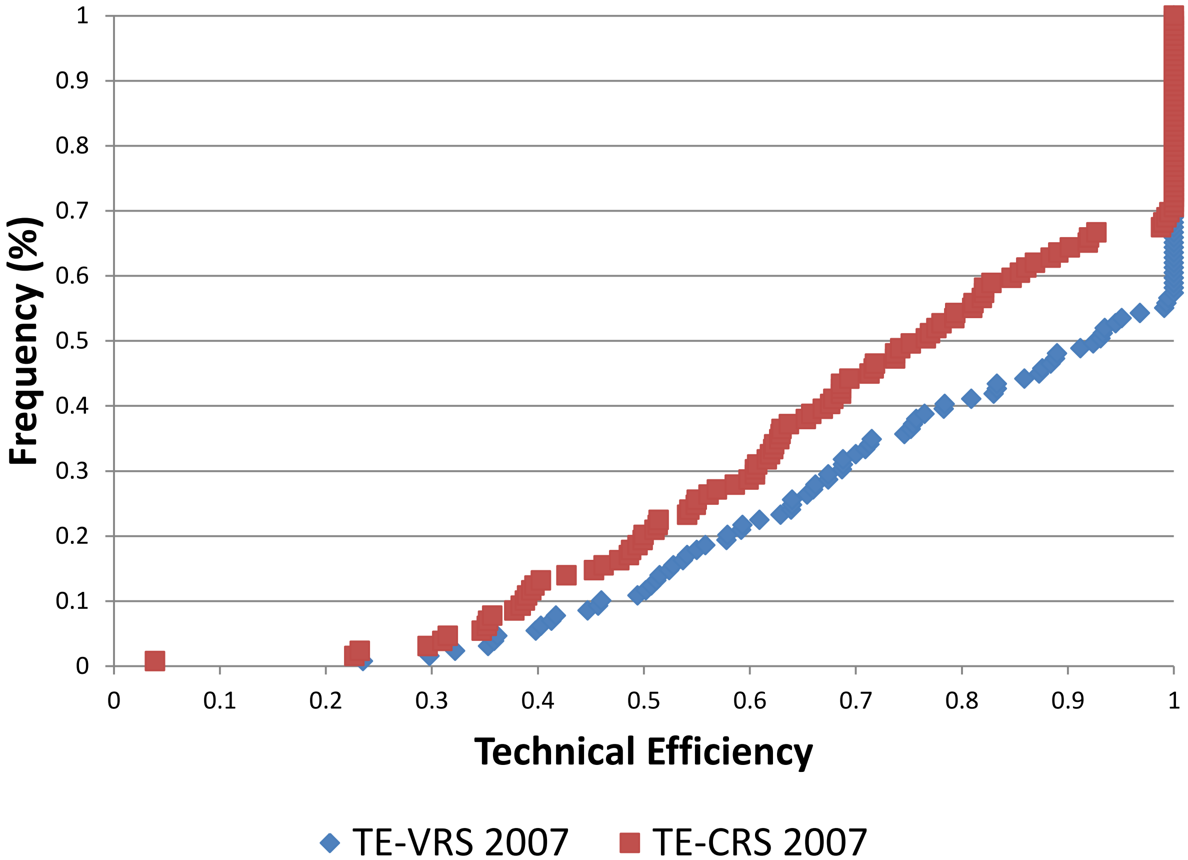


Table 4.2 Technical Efficiency Measures under VRS for a Sample of Kansas Farms

Summary Statistics		1993	1994	1995	1996	1997	1998
TE - VRS	Mean	0.83	0.91	0.90	0.91	0.93	0.92
	Min	0.13	0.44	0.36	0.42	0.32	0.30
	Max	1.00	1.00	1.00	1.00	1.00	1.00
	Std Dev	0.21	0.14	0.17	0.14	0.14	0.15
Distribution of Farms:							
TE-VRS < 0.40		6	0	3	0	2	1
0.40≤ TE-VRS < 0.50		6	3	2	1	0	3
0.50≤ TE-VRS < 0.60		10	3	9	6	6	3
0.60≤ TE-VRS < 0.70		11	8	5	8	3	7
0.70≤ TE-VRS < 0.80		13	17	11	11	8	8
0.80≤ TE-VRS < 0.90		13	11	8	18	12	14
0.90≤ TE-VRS < 1.00		6	11	7	9	15	6
TE-VRS = 1.00		64	76	84	76	83	87

Summary Statistics		1999	2000	2001	2002	2003	2004
TE - VRS	Mean	0.87	0.84	0.91	0.85	0.88	0.89
	Min	0.22	0.30	0.46	0.30	0.39	0.34
	Max	1.00	1.00	1.00	1.00	1.00	1.00
	Std Dev	0.20	0.20	0.13	0.19	0.17	0.16
Distribution of Farms:							
TE-VRS < 0.40		5	4	0	4	1	1
0.40≤ TE-VRS < 0.50		4	5	1	5	4	3
0.50≤ TE-VRS < 0.60		4	15	5	5	7	7
0.60≤ TE-VRS < 0.70		14	7	7	18	13	10
0.70≤ TE-VRS < 0.80		10	17	11	10	11	12
0.80≤ TE-VRS < 0.90		9	9	17	14	14	12
0.90≤ TE-VRS < 1.00		9	12	16	12	8	23
TE-VRS = 1.00		74	60	72	61	71	61

Table 4.2 Technical Efficiency Measures under VRS for a Sample of Kansas Farms (continued)

Summary Statistics		2005	2006	2007	2008	2009	2010	2011
TE - VRS	Mean	0.88	0.92	0.81	0.89	0.91	0.85	0.88
	Min	0.36	0.40	0.24	0.35	0.33	0.31	0.28
	Max	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Std Dev	0.17	0.14	0.22	0.17	0.15	0.19	0.18
Distribution of Farms:								
TE-VRS < 0.40		1	0	7	2	1	2	5
0.40≤ TE-VRS < 0.50		6	3	7	3	3	6	4
0.50≤ TE-VRS < 0.60		7	5	14	7	5	15	3
0.60≤ TE-VRS < 0.70		8	6	13	9	4	8	8
0.70≤ TE-VRS < 0.80		10	8	11	6	12	11	11
0.80≤ TE-VRS < 0.90		15	11	10	16	15	13	12
0.90≤ TE-VRS < 1.00		15	21	11	9	11	12	14
TE-VRS = 1.00		67	75	56	77	78	62	72

4.3 On-Farm Impacts of BES with Regression of TE_{VRS}

A linear regression was estimated in STATA as outlined in section 2.2.2 to examine the impact on observed TE_{VRS}[1] measures. A binary (0,1) variable [ADOPT] was used as a regressor where ADOPT equals 1 if the farm had adopted BES in period *t* or in a prior year of the analysis, and equal to 0 otherwise. The other independent variables in the linear regression analysis included a binary (0,1) dummy variable to account for a statewide negative yield event between 1993 and 2011. The variables W95, W00, W02, W03, and W11 are yearly dummy variables equal to 1 in 1995, 2000, 2002, 2003 and 2011, and 0 otherwise, respectively. These are the years when a statewide negative yield impact occurred with at least one of the primary crops (corn, soybeans, sorghum, or wheat) experiencing a statewide average yield per acre that was less than 80% of the preceding five-year moving average as reported by USDA-NASS (USDA-NASS, Quick Stats). A trend was also included in the regression, as well. The regression estimated is (following equation(25)):

(29) $TE_{VRS} = \beta_0 + \beta_1 (ADOPT) + \beta_2 (W95) + \beta_3 (W00) + \beta_4 (W02) + \beta_5 (W03) + \beta_6 (W11) + \beta_7 (TREND) + U$

The results of the regression analysis are presented in Table 4.3. The regression analysis indicated the coefficient on the dummy variable for adoption of BES (β_1) was significant at the 1% level and positively impacted TE_{VRS}. The marginal effect found running a Tobit model (as a robustness check) indicated a positive impact of the adoption of BES that was significant at the 10% level. Farms adopting BES would experience a 1.7% yield increase in their aggregate

[1] TE_{VRS} alone was considered rather than TE_{CRS} for this analysis for the reasons discussed in section 2.1. Further, the directional shifts seen in the results of section 4.2 comparing TE under VRS and CRS technologies were similar and impacts from BES adoption should be seen under the TE_{VRS} analysis if they are present.

outputs compared to similar non-adopting farms. The yield events in 2000 and 2002 were found to be negative and significant at the 1 and 5 percent levels, respectively. The trend was found to be negative and significant at the 5% level. This indicates that a farm observed later in the analysis would be expected to have a lower technical efficiency measure under VRS than if it were observed earlier in the study period and possibly a shifting of the frontier.

Table 4.3 Relationships Among Inefficiency, Marginal Effects, BES Adoption, Negative Yield Events, and Time

Independent Variable	Technical Efficiency - VRS	Marginal Effects Tobit
Intercept	0.838***	
	(0.010)	
Adoption of BES	0.026***	0.017*
	(0.009)	(0.009)
Negative Yield Event 1995	0.014	0.017
	(0.019)	(0.019)
Negative Yield Event 2000	-0.059***	-0.053***
	(0.018)	(0.018)
Negative Yield Event 2002	-0.046**	-0.045**
	(0.018)	(0.018)
Negative Yield Event 2003	0.002	0.003
	(0.018)	(0.018)
Negative Yield Event 2011	0.014	-0.020
	(0.020)	(0.020)
Trend	-0.002**	-0.002**
	(0.001)	(.001)

Note: Standard errors are in parentheses. Single, double, and triple asterisks (*) denote significance at the 10%, 5%, and 1% level, respectively.

The finding of positive impacts of BES adoption for on-farm technical efficiency builds further upon the existing literature. Fernandez-Cornejo, Hendricks, and Mishra (2005) found that BES adoption was positively related to off-farm labor – but with no impact on-farm. From this balanced panel of Kansas farms from 1993 through 2011, we conclude that in this sample there was evidence of a positive impact on on-farm technical efficiency of producing crops from of adopting BES. This indicates that there was a small increase in production from BES adopters.

Chapter 5 - Malmquist Productivity Change Index

The Malmquist productivity index (MI) under constant returns-to-scale (CRS) and the biennial Malmquist productivity index (BMI) under variable returns-to-scale (VRS) were estimated for the sample of Kansas farms in this study following the methods in section 2.3. All of the data envelopment analysis models for solving the problems and equations associated with computations of the MI were performed using GAMS. Problems (1), (3), (4), and (5) were solved as laid out in section 2.3.1. The results from the solution to those problems allowed for the computation of the MI under CRS (MI_{CRS}) for the sample farms (equation 6) in section 2.3.1. The results of efficiency change (EC) using equation (7) and the technical change (TC) according to the technique presented with equation (8) are presented. As discussed in section 2.3.2, assuming VRS technology for the models given by problems (2), (9), (10), and (11) that otherwise follow the model formulation in Färe et al. (1994) resulted in numerical infeasibilities preventing the computation of the MI under VRS, and a decomposition for TC. Accordingly, the study computed a biennial Malmquist productivity index under VRS (BMI_{VRS}) for each of the farms in the sample.

BMI_{VRS} calculations are presented using results from estimating problems (13) and (14) that were outlined in section 2.3.3 – and computing the ratio in equation (12). The decompositions for each farm in the biennial efficiency change (BEC) were computed using equation (15). Equations (12) and (15) and models for the Problems (13) and (14) were all solved using GAMS. The decomposition into the biennial technical change factor (BTC) was found using the relationship in (16) and was computed given the results from solving equations (12) and (15).

The comparison of the MI_{CRS} and BMI_{VRS} measures and their respective decompositions was performed using the Kolmogorov-Smirnov goodness-of-fit distributional hypothesis test (KS-test) as depicted in section 2.3.4. A two-sample t-test (T-test) determining if the population means of the two samples of measures for the MI_{CRS} and BMI_{VRS} and the respective decompositions into technical change and efficiency change are equal are also examined. The KS-tests and T-tests performed in this study were completed using MATLAB.

5.1 Malmquist Index – Constant Returns to Scale

The summary results of the MI_{CRS} measurements estimated for the farms in the study sample are presented in Table 5.1. The decomposition of MI_{CRS} into EC_{CRS} is summarized and presented in Table 5.2. The decomposition of MI_{CRS} into TC_{CRS} is summarized and presented in Table 5.3.

A MI or decomposition component less than 1 indicates a regress in productivity (Färe et al., 1994). We find in the summary of MI_{CRS} measurements in Table 5.1 that there was regress in productivity for at least half of the farms in this sample in 9 of the 18 year-over-year change periods represented in this analysis based on their MI_{CRS} measurements. Of the years with negative yield events as outlined in section 2.2.2 [1995, 2000, 2002, 2003, and 2011], only 2003 exhibited improvements in the relative productivity year-over-year for a majority of the farms in the analysis when compared to the year prior. This may be partially explained by 2003 following one of the other four negative yield event years. The 2002-2003 period was the only one during this analysis with two consecutive years where the mean yield per acre of at least one of the four primary crops reported by USDA-NASS was below 80% of the 5-year moving average. Examining the mean MI_{CRS} measurements, regress on average occurred for only 6 of the year-over-year periods. These periods include the second year being one of the four out of the five statewide negative yield events identified with only the 2002-2003 period having a mean MI_{CRS} across farms greater than 1.

The results summarized in Table 5.2 of the EC_{CRS} measures show that in 4 of the year-over-year change periods more than 50% of the farms exhibited a regress in efficiency change. These periods lined up with the same periods where the mean of EC_{CRS} measures indicated regress on average. Only the 2001-2002 year-to-year period indicated regress examining EC_{CRS} when the second year in the period coincided with a statewide negative yield event year as defined in section 2.2.2. The infrequency of this occurrence is not unexpected as a statewide yield event would be expected to lower productivity for farms on a systemic (wide) nature. Since EC_{CRS} is identified as "catching up" – in that it can represent DMUs moving closer to the efficient frontier – if all farms were impacted by a statewide negative yield event, it may not necessarily result in farms moving closer or further from the frontier in this analysis.

The cumulative distribution functions of the 1999 and 2000 technical efficiency measures under CRS are presented in Figure 5.1. Since the crop outputs of multiple farms would be expected to contract with a statewide negative yield event the distance between the observed farm output and the efficient frontier would not necessarily be expected to change. In Figure 5.1 we can see that there are farms in 1999 with technical efficiency measures lower than all those found for the sample in 2000. The farms' crop outputs in 1999 could be higher, but if the efficient farms have higher output than in 2000 with relatively the same input levels, the same inefficient farms could have a lower technical efficiency score in 1999 than in 2000. This condition could lead to a higher calculated efficiency change between the periods even with productivity decline. In this instance we would expect the productivity decline to be measured in the technical change.

The TC_{CRS} results summarized in Table 5.3 show 9 year-over-year periods where regress occurred for at least half of the farms in the period with estimated technical change less than 1. For eight of the year-over-year periods TC_{CRS} levels indicated a regress when examining the means of all farms TC_{CRS}. The only period with a second year corresponding with a statewide negative yield event identified for this analysis that did not coincide with a period on average showing regress from TC_{CRS} was 2002-2003. That occurrence could be that 2003 followed another identified statewide negative yield impact year.

Except for 2009-2010, when MI_{CRS} indicated regress with more than half the farms in the sample having a MI_{CRS} score less than 1, it was coupled with regress in the TC_{CRS} estimates. There were 12 periods when the MI or a decomposition component was less than 1 indicating regress, where at least half the farms for the period did not have a measure greater than or equal to 1. Examining the means for MI_{CRS}, EC_{CRS}, and TC_{CRS} we find there are 11 periods where there was regress in at least one of the measures evaluated.

The averages across the farms for MI_{CRS}, EC_{CRS}, and TC_{CRS} in the 2002-2003 period were all greater than 1. As can be seen in the cumulative distribution functions of the technical efficiency scores estimated for 2002 and 2003 (Figure 5.2) the technical efficiency scores are generally higher in 2003 than in 2002. This indicates that the productivity of farms generally increased in 2003, a negative statewide negative yield event year, with the efficient-frontier for this study year moving higher and the inefficient farms (on average) moving closer to the frontier.

Table 5.1 Malmquist Productivity Index Measures Under CRS for a Sample of Kansas Farms

Summary Statistics		1993-1994	1994-1995	1995-1996	1996-1997	1997-1998	1998-1999
Malmquist Index	Mean	1.281	0.802	1.473	1.081	0.951	1.120
Under CRS (MI-CRS)	Min	0.367	0.314	0.425	0.437	0.373	0.619
	Max	10.750	1.634	2.647	2.688	2.011	2.644
	Std Dev	0.939	0.263	0.443	0.359	0.308	0.308
Distribution of Farms:							
MI-CRS < 0.40		1	3	0	0	2	0
0.40≤ MI-CRS < 0.50		1	10	1	2	1	0
0.50≤ MI-CRS < 0.60		2	14	1	4	9	0
0.60≤ MI-CRS < 0.70		3	24	3	6	13	10
0.70≤ MI-CRS < 0.80		3	19	3	11	17	9
0.80≤ MI-CRS < 0.90		17	24	3	20	23	12
0.90≤ MI-CRS < 1.00		14	11	4	18	21	13
MI-CRS = 1.00		0	1	0	0	1	1
1.00< MI-CRS <1.10		15	7	9	14	12	17
1.10≤ MI-CRS <1.25		28	7	13	21	10	33
1.25≤ MI-CRS < 1.50		20	6	36	21	12	20
1.50≤ MI-CRS < 1.75		12	3	28	6	4	11
1.75≤ MI-CRS < 2.00		6	0	11	2	3	1
MI-CRS ≥ 2.00		7	0	17	4	1	2

Table 5.1 Malmquist Productivity Index Measures Under CRS for a Sample of Kansas Farms (continued)

Summary Statistics		1999-2000	2000-2001	2001-2002	2002-2003	2003-2004	2004-2005
Malmquist Index	Mean	0.985	1.108	0.904	1.202	1.305	1.045
Under CRS (MI-CRS)	Min	0.306	0.477	0.241	0.459	0.424	0.539
	Max	2.066	2.567	3.030	2.599	3.192	2.532
	Std Dev	0.314	0.395	0.363	0.395	0.438	0.308
Distribution of Farms:							
MI-CRS < 0.40		2	0	3	0	0	0
0.40≤ MI-CRS < 0.50		3	2	8	2	3	0
0.50≤ MI-CRS < 0.60		5	3	7	3	3	2
0.60≤ MI-CRS < 0.70		12	6	16	6	3	5
0.70≤ MI-CRS < 0.80		13	12	18	6	7	15
0.80≤ MI-CRS < 0.90		15	14	20	9	2	22
0.90≤ MI-CRS < 1.00		24	28	16	17	7	20
MI-CRS = 1.00		0	1	0	0	0	0
1.00< MI-CRS <1.10		19	12	15	14	10	23
1.10≤ MI-CRS <1.25		17	19	10	20	22	20
1.25≤ MI-CRS < 1.50		11	16	10	25	38	12
1.50≤ MI-CRS < 1.75		3	6	4	13	18	7
1.75≤ MI-CRS < 2.00		4	4	0	10	10	1
MI-CRS ≥ 2.00		1	6	2	4	6	2

Table 5.1 Malmquist Productivity Index Measures Under CRS for a Sample of Kansas Farms (continued)

Summary Statistics		2005-2006	2006-2007	2007-2008	2008-2009	2009-2010	2010-2011
Malmquist Index	Mean	0.886	1.187	1.408	1.024	1.024	0.981
Under CRS (MI-CRS)	Min	0.300	0.209	0.315	0.371	0.383	0.293
	Max	1.875	2.728	17.233	2.436	3.973	1.886
	Std Dev	0.258	0.431	1.513	0.371	0.522	0.327
Distribution of Farms:							
MI-CRS < 0.40		3	1	2	1	1	3
0.40≤ MI-CRS < 0.50		2	1	1	4	5	3
0.50≤ MI-CRS < 0.60		8	5	0	6	10	9
0.60≤ MI-CRS < 0.70		12	5	8	7	13	7
0.70≤ MI-CRS < 0.80		24	7	8	19	15	14
0.80≤ MI-CRS < 0.90		24	16	6	19	24	21
0.90≤ MI-CRS < 1.00		26	13	11	19	13	17
MI-CRS = 1.00		0	0	0	0	0	1
1.00< MI-CRS <1.10		7	12	15	11	9	12
1.10≤ MI-CRS <1.25		12	21	22	12	13	13
1.25≤ MI-CRS < 1.50		8	23	26	19	13	21
1.50≤ MI-CRS < 1.75		2	12	14	5	4	5
1.75≤ MI-CRS < 2.00		1	8	6	4	2	3
MI-CRS ≥ 2.00		0	5	10	3	7	0

Table 5.2 Efficiency Change Measures Under CRS for a Sample of Kansas Farms

Summary Statistics		1993-1994	1994-1995	1995-1996	1996-1997	1997-1998	1998-1999
Efficiency Change	Mean	1.204	1.025	1.032	1.078	1.013	0.918
Decomposed (EC-CRS)	Min	0.622	0.500	0.360	0.479	0.424	0.379
	Max	7.783	1.804	2.335	3.117	1.830	1.424
	Std Dev	0.683	0.239	0.265	0.277	0.215	0.199
Distribution of Farms:							
EC-CRS < 0.40		0	0	1	0	0	1
0.40≤ EC-CRS < 0.50		0	0	2	1	1	3
0.50≤ EC-CRS < 0.60		0	3	0	0	1	7
0.60≤ EC-CRS < 0.70		2	9	3	2	5	9
0.70≤ EC-CRS < 0.80		6	7	10	1	10	14
0.80≤ EC-CRS < 0.90		11	12	11	16	11	18
0.90≤ EC-CRS < 0.90		11	13	18	18	14	14
EC-CRS = 1.00		36	38	37	41	48	37
1.00< EC-CRS < 1.10		16	16	17	10	10	9
1.10≤ EC-CRS < 1.25		13	10	11	18	16	11
1.25≤ EC-CRS < 1.50		16	15	11	16	10	6
1.50≤ EC-CRS < 1.75		8	5	5	4	1	0
1.75≤ EC-CRS < 2.00		3	1	2	0	2	0
EC-CRS ≥ 2.00		7	0	1	2	0	0

Table 5.2 Efficiency Change Measures Under CRS for a Sample of Kansas Farms (continued)

Summary Statistics		1999-2000	2000-2001	2001-2002	2002-2003	2003-2004	2004-2005
Efficiency Change	Mean	1.008	1.177	0.930	1.106	1.023	1.024
Decomposed (EC-CRS)	Min	0.415	0.613	0.326	0.410	0.366	0.405
	Max	2.412	3.093	1.907	2.063	1.941	2.210
	Std Dev	0.282	0.357	0.240	0.287	0.252	0.282
Distribution of Farms:							
EC-CRS < 0.40		0	0	2	0	1	0
0.40≤ EC-CRS < 0.50		1	0	2	1	1	2
0.50≤ EC-CRS < 0.60		4	0	6	2	3	3
0.60≤ EC-CRS < 0.70		6	3	8	3	6	9
0.70≤ EC-CRS < 0.80		16	6	21	6	7	8
0.80≤ EC-CRS < 0.90		11	9	18	9	17	15
0.90≤ EC-CRS < 0.90		18	13	10	19	22	17
EC-CRS = 1.00		27	28	26	26	25	24
1.00< EC-CRS < 1.10		17	13	12	12	9	17
1.10≤ EC-CRS < 1.25		8	14	11	19	16	15
1.25≤ EC-CRS < 1.50		15	21	12	20	14	12
1.50≤ EC-CRS < 1.75		3	15	0	7	7	4
1.75≤ EC-CRS < 2.00		1	5	1	3	1	2
EC-CRS ≥ 2.00		2	2	0	2	0	1

Table 5.2 Efficiency Change Measures Under CRS for a Sample of Kansas Farms (continued)

Summary Statistics		2005-2006	2006-2007	2007-2008	2008-2009	2009-2010	2010-2011
Efficiency Change	Mean	1.133	0.831	1.399	1.046	0.950	1.115
Decomposed (EC-CRS)	Min	0.449	0.118	0.451	0.429	0.398	0.389
	Max	2.522	1.721	21.318	2.323	2.516	2.463
	Std Dev	0.309	0.232	1.840	0.303	0.326	0.349
Distribution of Farms:							
EC-CRS < 0.40		0	5	0	0	1	1
0.40≤ EC-CRS < 0.50		1	6	1	5	2	1
0.50≤ EC-CRS < 0.60		1	11	1	0	6	4
0.60≤ EC-CRS < 0.70		5	15	2	4	16	5
0.70≤ EC-CRS < 0.80		1	13	9	12	15	6
0.80≤ EC-CRS < 0.90		3	21	3	10	19	10
0.90≤ EC-CRS < 0.90		13	14	8	14	13	10
EC-CRS = 1.00		36	33	31	35	26	31
1.00< EC-CRS < 1.10		22	2	14	14	7	11
1.10≤ EC-CRS < 1.25		18	8	17	13	12	15
1.25≤ EC-CRS < 1.50		14	0	16	12	7	15
1.50≤ EC-CRS < 1.75		9	1	13	5	1	13
1.75≤ EC-CRS < 2.00		3	0	5	3	1	5
EC-CRS ≥ 2.00		3	0	9	2	3	2

Figure 5.1 Cumulative Distribution Functions of Technical Efficiency Measures under CRS in 1999 and 2000 for a Sample of Kansas Farms

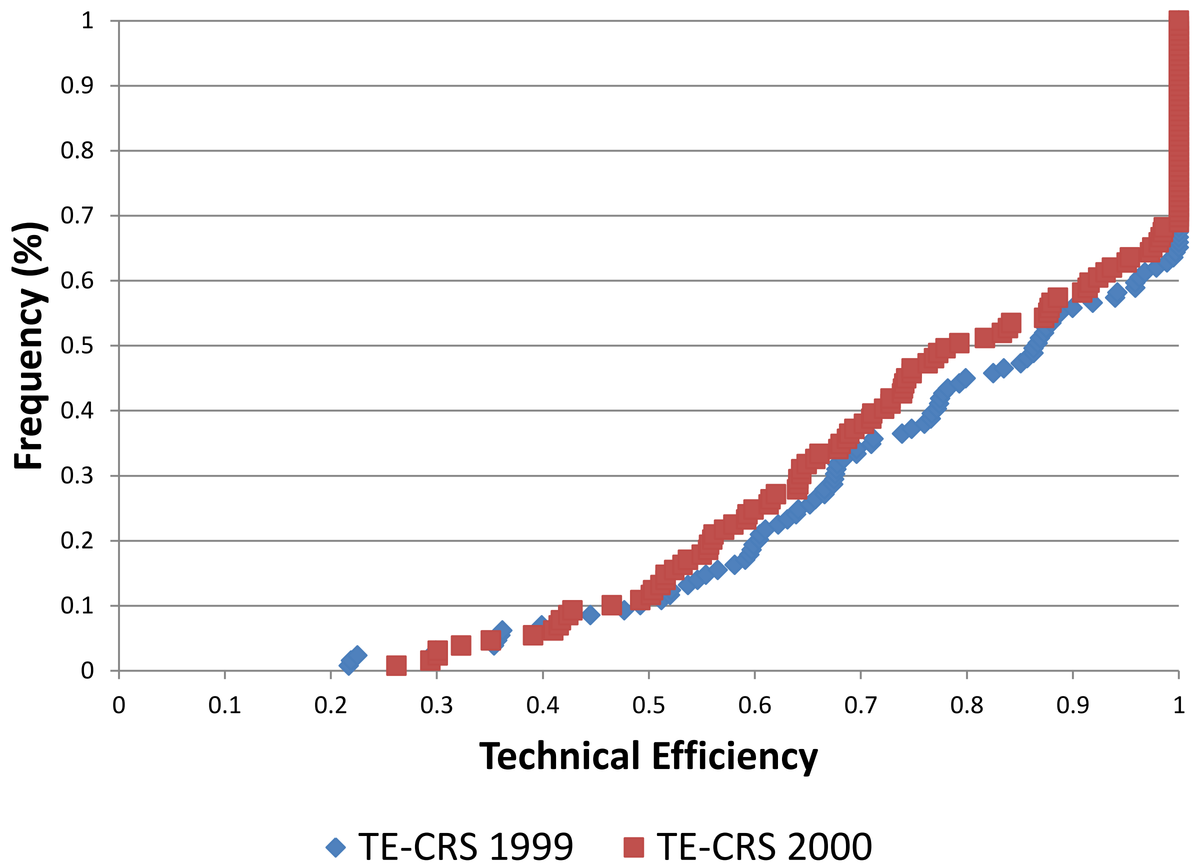


Figure 5.2 Cumulative Distribution Functions of Technical Efficiency Measures under CRS in 2002 and 2003 for a Sample of Kansas Farms

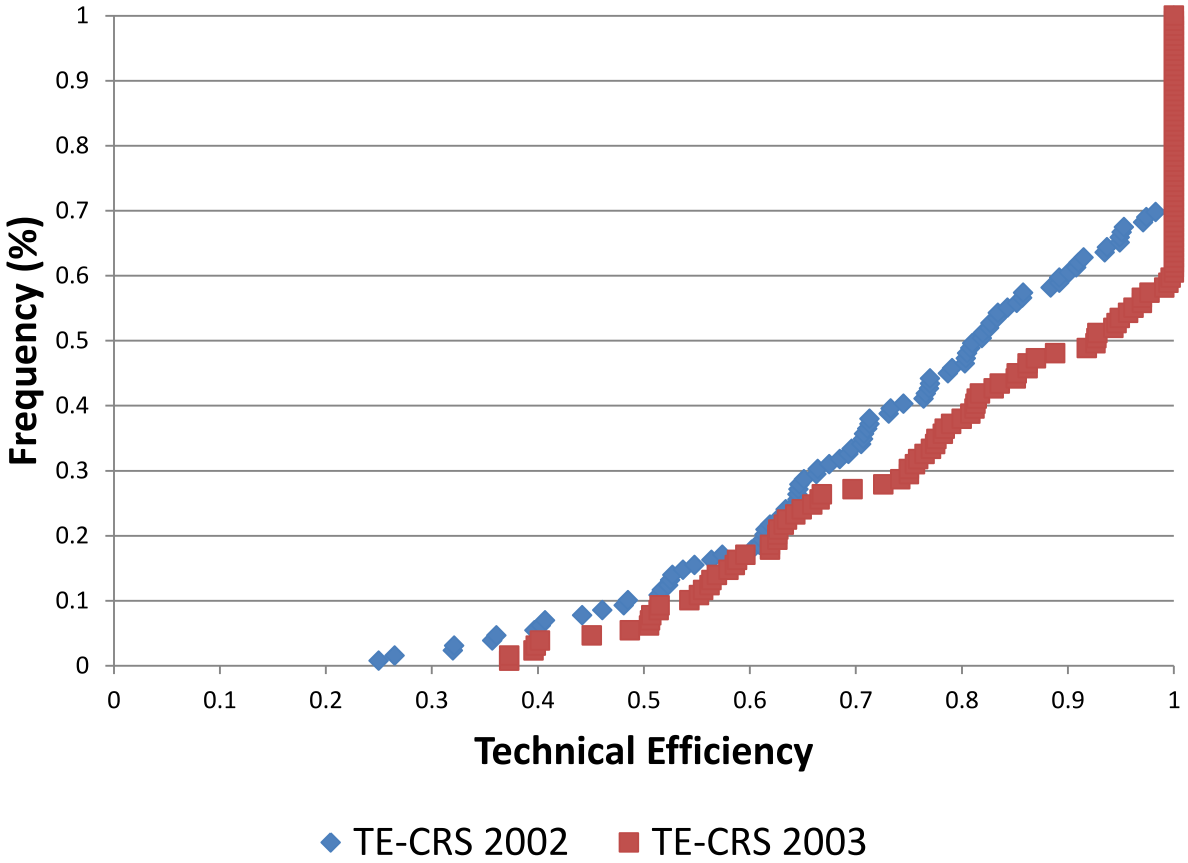


Table 5.3 Technical Change Measures Under CRS for a Sample of Kansas Farms

Summary Statistics		1993-1994	1994-1995	1995-1996	1996-1997	1997-1998	1998-1999
Technical Change	Mean	1.070	0.786	1.434	1.003	0.937	1.237
(TC-CRS)	Min	0.497	0.401	0.736	0.489	0.571	0.774
	Max	2.420	1.552	2.647	2.020	1.989	2.644
	Std Dev	0.290	0.198	0.313	0.228	0.230	0.280
Distribution of Farms:							
TC-CRS < 0.40		0	0	0	0	0	0
0.40≤ TC-CRS < 0.50		1	4	0	1	0	0
0.50≤ TC-CRS < 0.60		3	13	0	3	2	0
0.60≤ TC-CRS < 0.70		3	32	0	3	8	0
0.70≤ TC-CRS < 0.80		9	32	3	10	25	2
0.80≤ TC-CRS < 0.90		19	19	2	24	32	4
0.90≤ MI-CRS < 1.00		18	8	2	29	27	9
MI-CRS = 1.00		0	0	0	0	1	0
1.00< MI-CRS < 1.10		25	9	5	22	13	30
1.10≤ MI-CRS < 1.25		25	8	16	21	11	35
1.25≤ MI-CRS < 1.50		18	3	61	13	6	34
1.50≤ MI-CRS < 1.75		5	1	25	1	2	8
1.75≤ MI-CRS < 2.00		1	0	9	1	2	4
MI-CRS ≥ 2.00		2	0	6	1	0	3

Table 5.3 Technical Change Measures Under CRS for a Sample of Kansas Farms (continued)

Summary Statistics		1999-2000	2000-2001	2001-2002	2002-2003	2003-2004	2004-2005
Technical Change	Mean	0.982	0.947	0.965	1.080	1.280	1.038
(TC-CRS)	Min	0.408	0.477	0.546	0.541	0.563	0.612
	Max	1.777	1.823	3.030	1.607	3.192	1.905
	Std Dev	0.199	0.207	0.261	0.183	0.337	0.198
Distribution of Farms:							
TC-CRS < 0.40		0	0	0	0	0	0
0.40≤ TC-CRS < 0.50		1	1	0	0	0	0
0.50≤ TC-CRS < 0.60		3	4	3	1	1	0
0.60≤ TC-CRS < 0.70		1	6	5	0	0	2
0.70≤ TC-CRS < 0.80		9	17	18	3	5	11
0.80≤ TC-CRS < 0.90		27	26	26	14	3	17
0.90≤ MI-CRS < 1.00		34	30	28	28	13	25
MI-CRS = 1.00		0	1	0	0	0	0
1.00< MI-CRS < 1.10		28	22	27	34	14	34
1.10≤ MI-CRS < 1.25		18	11	13	25	28	23
1.25≤ MI-CRS < 1.50		5	10	6	20	41	13
1.50≤ MI-CRS < 1.75		1	0	2	4	14	3
1.75≤ MI-CRS < 2.00		2	1	0	0	6	1
MI-CRS ≥ 2.00		0	0	1	0	4	0

Table 5.3 Technical Change Measures Under CRS for a Sample of Kansas Farms (continued)

Summary Statistics		2005-2006	2006-2007	2007-2008	2008-2009	2009-2010	2010-2011
Technical Change	Mean	0.784	1.440	1.051	0.978	1.068	0.893
(TC-CRS)	Min	0.364	0.548	0.458	0.511	0.467	0.307
	Max	1.089	2.648	3.410	1.763	2.432	1.566
	Std Dev	0.117	0.307	0.359	0.203	0.298	0.211
Distribution of Farms:							
TC-CRS < 0.40		1	0	0	0	0	1
0.40≤ TC-CRS < 0.50		1	0	1	0	1	1
0.50≤ TC-CRS < 0.60		3	1	1	3	1	3
0.60≤ TC-CRS < 0.70		21	0	7	1	4	14
0.70≤ TC-CRS < 0.80		48	0	12	17	14	24
0.80≤ TC-CRS < 0.90		37	4	15	24	21	34
0.90≤ MI-CRS < 1.00		14	3	28	33	21	19
MI-CRS = 1.00		0	0	0	1	0	2
1.00< MI-CRS < 1.10		4	8	16	24	13	12
1.10≤ MI-CRS < 1.25		0	20	26	19	29	9
1.25≤ MI-CRS < 1.50		0	39	19	3	14	9
1.50≤ MI-CRS < 1.75		0	36	2	2	6	1
1.75≤ MI-CRS < 2.00		0	14	0	2	3	0
MI-CRS ≥ 2.00		0	4	2	0	2	0

5.2 Biennial Malmquist Index – Variable Returns to Scale

As presented in section 2.3.2, the application of the Färe et al. (1997) technique in developing and decomposing the MI when assuming VRS resulted in numerical infeasibilities. Therefore the biennial Malmquist index (BMI) was used as proposed by Pastor, Asmild, and Lovell (2011).

The summary results of the BMI_{VRS} measurements estimated for the sample farms in each year in the analysis are presented in Table 5.4. The BMI_{VRS} decomposition into BEC_{VRS} is summarized and presented for this study in Table 5.5. The BMI_{VRS} decomposition into BTC_{VRS} is summarized and presented for this study in Table 5.6.

A BMI_{VRS} measure less than 1 indicates productivity regress with the farm's second year data observed being further from the estimated efficient biennial frontier than the farm's first year observed data. Three of the biennial periods indicate a productivity decline when 50% or more of the farms were estimated to have a BMI_{VRS} less than 1. These periods were 1994-1995; 1999-2000; and 2001-2002. Each of these biennial periods correspond with the second year having been one of the identified negative statewide negative yield impacts in the analysis. The number of biennial periods showing productivity declines is less when compared to analysis examining MI_{CRS} when counting the periods when half or more of the farms have a productivity index less than 1. However, when examining the mean of the BMI_{VRS} scores for each year, more periods demonstrate productivity regress under VRS than under the MI analysis assuming CRS. The additional periods indicating regress with the average of the BMI_{VRS} scores less than 1 is 2009-2010. In 2009-2010, the maximum BMI_{VRS} is 2.696, while the maximum MI_{CRS} is 3.973. A larger change is possible for an individual efficient firm being analyzed under CRS when others are forced to be compared to that efficient unit regardless of size. Of the 18 periods examined within this analysis of BMI_{VRS}, 7 would indicate productivity regress on average, based on the mean BMI_{VRS} estimates across farms for that period. This result is compared with 6 year-over-year periods with regress indicated using mean estimates from the MI_{CRS}. Again in the BMI analysis, the period with 2003 as the second year was the only one with the second year considered a negative statewide negative yield impact where the mean BMI_{VRS} was found to be greater than 1.

The results summarized in Table 5.5 of the BEC_{VRS} indicate that 2006-2007 is the only biennial period with more than half of the farms exhibiting productivity regress as indicated by the level of BEC_{VRS}. Five biennial periods indicated productivity regress based on the mean BEC_{VRS} across sample farms.

The BTC_{VRS} results summarized in Table 5.6 show three periods that exhibit productivity regress, where more than half the farms in the summary were found with BTC_{VRS} measures estimated to be less than 1. Two of those periods, 1994-1995 and 2001-2002 correspond with assumed negative yield event years as the second year in the period. When estimating productivity decline using the means of the farm's BTC_{VRS} measures, we find 8 periods showing regress. Those include the four expected periods with the second year corresponding to a statewide negative yield impact. Again the biennial period missing from the list of those indicating regress that have the second year corresponding to a statewide negative yield impact as outlined in section 2.2.2 is 2002-2003.

The periods with regress indicated examining the means of all the sample farms is identical between the MI-TC and BMI-BTC. The periods indicating regress under the MI-TC analysis are higher than under BMI-TC, likely due to the tighter envelopment of observations with the convexity constraints under VRS than when CRS is assumed as highlighted in section 2.1.

There were 11 periods where the BMI or a decomposition component mean was less than 1 indicating regress when examining the means of the farms' measures in this analysis. The 11 biennial periods indicating regress through the means included the 5 periods with productivity regress indicated in at least one of the measures, given at least half of the farms in that period demonstrated declines. These same 11 periods matched exactly with the periods where the MI or a decomposition component mean was less than 1, indicating regress.

The results found for the Malmquist productivity indices and decompositions of efficiency change and technical change under CRS and VRS are examined further for differences in section 5.3 using statistical tests. Per the discussion in section 2.1, this study assumes benefits derived from assuming VRS over CRS, which provides convenience of computations in this analysis of efficiency measures. The efficiency measures developed under the biennial Malmquist productivity analysis and subsequent decompositions into efficiency change and technical change will be used to examine the impacts of BES adoption. First we examine the motivation and need for examining these changes under VRS rather than CRS by examining the differences obtained under CRS and VRS in section 5.3.

Table 5.4 Biennial Malmquist Productivity Index Under VRS for a Sample of Kansas Farms

Summary Statistics		1993-1994	1994-1995	1995-1996	1996-1997	1997-1998	1998-1999
Biennial Malmquist	Mean	1.229	0.867	1.278	1.042	0.969	1.028
Index	Min	0.698	0.332	0.209	0.419	0.411	0.558
Under VRS (BMI-VRS)	Max	8.065	1.637	3.111	1.877	1.862	1.931
	Std Dev	0.696	0.224	0.400	0.210	0.211	0.210
Distribution of Farms:							
BMI-VRS < 0.40		0	1	1	0	0	0
0.40≤ BMI-VRS < 0.50		0	4	1	1	2	0
0.50≤ BMI-VRS < 0.60		0	11	0	1	1	2
0.60≤ BMI-VRS < 0.70		1	15	0	1	10	6
0.70≤ BMI-VRS < 0.80		7	19	0	9	12	9
0.80≤ BMI-VRS < 0.90		9	19	6	11	11	4
0.90≤ BMI-VRS < 1.00		7	11	8	15	19	16
BMI-VRS = 1.00		33	26	27	45	49	43
1.00< BMI-VRS < 1.10		16	13	14	10	7	15
1.10≤ BMI-VRS < 1.25		20	4	19	16	10	18
1.25≤ BMI-VRS < 1.50		18	5	23	16	4	13
1.50≤ BMI-VRS < 1.75		5	1	12	2	3	1
1.75≤ BMI-VRS < 2.00		6	0	10	2	1	2
BMI-VRS ≥ 2.00		7	0	8	0	0	0

Table 5.4 Biennial Malmquist Productivity Index Measures Under VRS for a Sample of Kansas Farms (continued)

Summary Statistics		1999-2000	2000-2001	2001-2002	2002-2003	2003-2004	2004-2005
Biennial Malmquist	Mean	0.957	1.102	0.912	1.133	1.145	1.045
Index	Min	0.453	0.590	0.401	0.508	0.388	0.560
Under VRS (BMI-VRS)	Max	1.976	2.299	1.574	1.990	2.045	2.488
	Std Dev	0.233	0.282	0.227	0.302	0.316	0.257
Distribution of Farms:							
BMI-VRS < 0.40		0	0	0	0	1	0
0.40≤ BMI-VRS < 0.50		2	0	7	0	2	0
0.50≤ BMI-VRS < 0.60		4	2	4	3	2	1
0.60≤ BMI-VRS < 0.70		10	2	9	5	4	3
0.70≤ BMI-VRS < 0.80		11	5	22	6	4	13
0.80≤ BMI-VRS < 0.90		19	13	15	4	5	11
0.90≤ BMI-VRS < 1.00		19	16	13	19	10	15
BMI-VRS = 1.00		33	34	34	25	33	38
1.00< BMI-VRS < 1.10		10	10	7	14	8	16
1.10≤ BMI-VRS < 1.25		11	18	9	15	21	15
1.25≤ BMI-VRS < 1.50		6	18	8	20	23	12
1.50≤ BMI-VRS < 1.75		2	7	1	13	10	3
1.75≤ BMI-VRS < 2.00		2	1	0	5	4	0
BMI-VRS ≥ 2.00		0	3	0	0	2	2

Table 5.4 Biennial Malmquist Productivity Index Measures Under VRS for a Sample of Kansas Farms (continued)

Summary Statistics		2005-2006	2006-2007	2007-2008	2008-2009	2009-2010	2010-2011
Biennial Malmquist	Mean	0.939	1.085	1.248	1.034	0.984	0.997
Index	Min	0.224	0.501	0.414	0.377	0.395	0.357
Under VRS (BMI-VRS)	Max	1.900	3.115	3.497	2.230	2.696	2.268
	Std Dev	0.222	0.361	0.475	0.287	0.334	0.297
Distribution of Farms:							
BMI-VRS < 0.40		1	0	0	1	1	1
0.40≤ BMI-VRS < 0.50		3	0	1	2	3	3
0.50≤ BMI-VRS < 0.60		4	5	1	3	1	5
0.60≤ BMI-VRS < 0.70		8	6	2	3	15	9
0.70≤ BMI-VRS < 0.80		12	6	5	9	17	14
0.80≤ BMI-VRS < 0.90		19	15	5	13	14	10
0.90≤ BMI-VRS < 1.00		15	13	9	16	13	12
BMI-VRS = 1.00		37	30	36	38	27	34
1.00< BMI-VRS < 1.10		14	9	10	14	9	7
1.10≤ BMI-VRS < 1.25		6	20	15	8	12	15
1.25≤ BMI-VRS < 1.50		8	11	18	14	11	14
1.50≤ BMI-VRS < 1.75		1	8	10	4	2	3
1.75≤ BMI-VRS < 2.00		1	2	9	1	1	0
BMI-VRS ≥ 2.00		0	4	8	3	3	2

Table 5.5 Biennial Efficiency Change Measures Under VRS for a Sample of Kansas Farms

Summary Statistics		1993-1994	1994-1995	1995-1996	1996-1997	1997-1998	1998-1999
Biennial Efficiency Change	Mean	1.190	1.001	1.034	1.035	1.004	0.952
BEC-VRS	Min	0.647	0.513	0.507	0.507	0.396	0.394
	Max	7.752	1.786	1.916	1.972	1.972	1.416
	Std Dev	0.666	0.195	0.192	0.157	0.191	0.180
Distribution of Farms:							
BEC-VRS < 0.40		0	0	0	0	1	1
0.40≤ BEC-VRS < 0.50		0	0	0	0	0	2
0.50≤ BEC-VRS < 0.60		0	4	1	1	1	4
0.60≤ BEC-VRS < 0.70		1	6	0	1	4	5
0.70≤ BEC-VRS < 0.80		4	6	3	2	6	12
0.80≤ BEC-VRS < 0.90		9	10	15	8	9	9
0.90≤ BEC-VRS < 1.00		9	9	14	15	8	11
BEC-VRS = 1.00		55	61	63	63	71	66
1.00< BEC-VRS < 1.10		8	9	9	12	13	4
1.10≤ BEC-VRS < 1.25		9	9	8	16	8	9
1.25≤ BEC-VRS < 1.50		17	13	12	10	5	6
1.50≤ BEC-VRS < 1.75		10	1	3	0	1	0
1.75≤ BEC-VRS < 2.00		2	1	1	1	2	0
BEC-VRS ≥ 2.00		5	0	0	0	0	0

Table 5.5 Biennial Efficiency Change Measures Under VRS for a Sample of Kansas Farms (continued)

Summary Statistics		1999-2000	2000-2001	2001-2002	2002-2003	2003-2004	2004-2005
Biennial Efficiency Change	Mean	0.979	1.148	0.936	1.071	1.027	1.022
BEC-VRS	Min	0.455	0.735	0.438	0.386	0.423	0.447
	Max	1.869	2.657	1.936	2.047	1.581	2.017
	Std Dev	0.204	0.282	0.203	0.247	0.197	0.241
Distribution of Farms:							
BEC-VRS < 0.40		0	0	0	1	0	0
0.40≤ BEC-VRS < 0.50		1	0	2	0	1	1
0.50≤ BEC-VRS < 0.60		3	0	5	0	2	1
0.60≤ BEC-VRS < 0.70		5	0	11	4	3	5
0.70≤ BEC-VRS < 0.80		16	2	14	7	6	12
0.80≤ BEC-VRS < 0.90		8	11	14	10	10	13
0.90≤ BEC-VRS < 1.00		16	7	7	9	20	9
BEC-VRS = 1.00		51	47	49	47	41	50
1.00< BEC-VRS < 1.10		10	14	11	12	15	10
1.10≤ BEC-VRS < 1.25		9	11	10	14	14	8
1.25≤ BEC-VRS < 1.50		7	20	5	16	14	15
1.50≤ BEC-VRS < 1.75		2	13	0	7	3	2
1.75≤ BEC-VRS < 2.00		1	3	1	1	0	2
BEC-VRS ≥ 2.00		0	1	0	1	0	1

Table 5.5 Biennial Efficiency Change Measures Under VRS for a Sample of Kansas Farms (continued)

Summary Statistics		2005-2006	2006-2007	2007-2008	2008-2009	2009-2010	2010-2011
Biennial Efficiency Change	Mean	1.070	0.889	1.189	1.054	0.943	1.080
BEC-VRS	Min	0.433	0.248	0.470	0.335	0.404	0.431
	Max	2.510	1.656	4.255	2.185	2.755	2.110
	Std Dev	0.249	0.209	0.460	0.259	0.267	0.274
Distribution of Farms:							
BEC-VRS < 0.40		0	4	0	1	0	0
0.40≤ BEC-VRS < 0.50		1	3	1	0	3	2
0.50≤ BEC-VRS < 0.60		2	9	1	2	4	0
0.60≤ BEC-VRS < 0.70		3	10	4	2	10	6
0.70≤ BEC-VRS < 0.80		1	10	1	6	13	5
0.80≤ BEC-VRS < 0.90		3	10	8	9	12	7
0.90≤ BEC-VRS < 1.00		17	20	6	8	17	10
BEC-VRS = 1.00		56	48	47	63	48	50
1.00< BEC-VRS < 1.10		14	8	11	10	10	11
1.10≤ BEC-VRS < 1.25		14	5	16	11	6	16
1.25≤ BEC-VRS < 1.50		10	1	12	10	2	9
1.50≤ BEC-VRS < 1.75		6	1	13	2	2	10
1.75≤ BEC-VRS < 2.00		1	0	5	2	1	1
BEC-VRS ≥ 2.00		1	0	4	3	1	2

Table 5.6 Biennial Technical Change Measures Under VRS for a Sample of Kansas Farms

Summary Statistics		1993-1994	1994-1995	1995-1996	1996-1997	1997-1998	1998-1999
Biennial Technical	Mean	1.045	0.867	1.226	1.007	0.966	1.095
Change	Min	0.548	0.467	0.209	0.586	0.734	0.558
BTC-VRS	Max	1.692	1.368	1.931	1.446	1.631	2.158
	Std Dev	0.186	0.163	0.250	0.126	0.120	0.188
Distribution of Farms:							
BTC-VRS < 0.40		0	0	1	0	0	0
0.40≤ BTC-VRS < 0.50		0	1	0	0	0	0
0.50≤ BTC-VRS < 0.60		1	2	0	1	0	1
0.60≤ BTC-VRS < 0.70		1	20	0	2	0	0
0.70≤ BTC-VRS < 0.80		9	29	0	4	14	2
0.80≤ BTC-VRS < 0.90		9	19	1	13	20	1
0.90≤ BTC-VRS < 1.00		18	15	8	15	20	12
BTC-VRS = 1.00		34	26	29	48	50	43
1.00 < BTC-VRS < 1.10		25	10	9	23	16	26
1.10 ≤ BTC-VRS < 1.25		10	4	24	19	7	23
1.25 ≤ BTC-VRS < 1.50		21	3	41	4	1	16
1.50 ≤ BTC-VRS < 1.75		1	0	11	0	1	4
1.75 ≤ BTC-VRS < 2.00		0	0	5	0	0	0
BTC-VRS ≥ 2.00		0	0	0	0	0	1

Table 5.6 Biennial Technical Change Measures Under VRS for a Sample of Kansas Farms (continued)

Summary Statistics		1999-2000	2000-2001	2001-2002	2002-2003	2003-2004	2004-2005
Biennial Technical	Mean	0.980	0.966	0.974	1.059	1.110	1.031
Change	Min	0.628	0.569	0.632	0.659	0.701	0.789
BTC-VRS	Max	1.498	1.301	1.495	1.647	1.878	1.403
	Std Dev	0.141	0.133	0.135	0.161	0.207	0.127
Distribution of Farms:							
BTC-VRS < 0.40		0	0	0	0	0	0
0.40≤ BTC-VRS < 0.50		0	0	0	0	0	0
0.50≤ BTC-VRS < 0.60		0	3	0	0	0	0
0.60≤ BTC-VRS < 0.70		2	2	4	1	0	0
0.70≤ BTC-VRS < 0.80		9	9	6	1	4	2
0.80≤ BTC-VRS < 0.90		20	17	27	9	8	12
0.90≤ BTC-VRS < 1.00		30	21	29	32	9	26
BTC-VRS = 1.00		36	36	34	25	34	37
1.00 < BTC-VRS < 1.10		17	29	13	23	23	23
1.10 ≤ BTC-VRS < 1.25		9	10	11	22	25	16
1.25 ≤ BTC-VRS < 1.50		6	2	5	14	19	13
1.50 ≤ BTC-VRS < 1.75		0	0	0	2	4	0
1.75 ≤ BTC-VRS < 2.00		0	0	0	0	3	0
BTC-VRS ≥ 2.00		0	0	0	0	0	0

Table 5.6 Biennial Technical Change Measures Under VRS for a Sample of Kansas Farms (continued)

Summary Statistics		2005-2006	2006-2007	2007-2008	2008-2009	2009-2010	2010-2011
Biennial Technical	Mean	0.882	1.237	1.055	0.983	1.047	0.930
Change	Min	0.490	0.848	0.620	0.459	0.669	0.424
BTC-VRS	Max	1.194	2.063	2.020	1.374	2.336	1.658
	Std Dev	0.130	0.286	0.166	0.132	0.223	0.181
Distribution of Farms:							
BTC-VRS < 0.40		0	0	0	0	0	0
0.40≤ BTC-VRS < 0.50		1	0	0	1	0	2
0.50≤ BTC-VRS < 0.60		3	0	0	0	0	3
0.60≤ BTC-VRS < 0.70		6	0	1	2	1	10
0.70≤ BTC-VRS < 0.80		25	0	3	10	5	13
0.80≤ BTC-VRS < 0.90		28	2	10	15	17	21
0.90≤ BTC-VRS < 1.00		20	12	16	22	26	13
BTC-VRS = 1.00		39	31	36	38	29	36
1.00 < BTC-VRS < 1.10		6	13	25	19	15	22
1.10 ≤ BTC-VRS < 1.25		1	21	25	20	22	5
1.25 ≤ BTC-VRS < 1.50		0	25	11	2	9	3
1.50 ≤ BTC-VRS < 1.75		0	16	1	0	2	1
1.75 ≤ BTC-VRS < 2.00		0	6	0	0	2	0
BTC-VRS ≥ 2.00		0	3	1	0	1	0

5.3 A Comparison of Constant Returns-to-Scale and Variable Returns-to-Scale for Malmquist Index Measures

Developing an empirical understanding of potential differences that may arise in estimated efficiency and productivity measures from models assuming either CRS or VRS is important for providing insights to the usefulness of the modeling techniques available. Furthermore, a comparison of the impact of assuming CRS when VRS may be the true technology is worthwhile to estimate the bias that may then occur in such an analysis. The empirical cumulative distribution functions for the MI_{CRS} and BMI_{VRS} and their respective decompositions into technical change and efficiency change were estimated and tested using MATLAB to determine if there is evidence of the measures being significantly different. Three two-sample Kolmogorov-Smirnov goodness-of-fit hypothesis tests (KS-tests) were performed comparing the empirical cumulative distribution functions for MI_{CRS} and BMI_{VRS}; EC_{CRS} and BEC_{VRS}; and TC_{CRS} and BTC_{VRS}. A two-sample t-test (T-test) was performed to determine if the population means of each of the same empirical cumulative distribution functions of comparison pairs are equal. The first test provides an examination if the distribution of efficiency measures across farms is equivalent, while the second test examines if the processes of developing the empirical cumulative distribution functions for each pair were equivalent (NIST/SEMATECH, 2015). The results of the T-test also provide an estimate of bias that exists if the KS-tests indicate the samples results are significantly different. The summary results of the tests are presented in Table 5.7.

At the 10% significance level, only the comparison between MI_{CRS} and BMI_{VRS} in 2004-2005 failed to reject that the empirical cumulative distribution functions for each was drawn from the same population. Thus, for 17 of the periods analyzed for this sample, there is evidence that the results under CRS and VRS using the MI_{CRS} and BMI_{VRS} techniques are statistically different. Given the T-test results for 2004-2005, we fail to reject that the means of the empirical cumulative distribution functions are equal, as well. The T-tests comparing the means of the empirical cumulative distribution functions of MI_{CRS} and BMI_{VRS} rejected that the means are equal in 6 of the periods.

There was only a statistical difference in the empirical cumulative distribution functions generated between the EC_{CRS} and the BEC_{VRS} for three periods: 1998-1999; 2005-2006; and 2006-2007. The T-test for comparing the means of the empirical cumulative distribution functions generated by the EC_{CRS} and the BEC_{VRS} in this analysis only provide evidence at the 10% level of significance for rejecting the means being equal once in 2006-2007. The relatively fewer statistical differences in the empirical cumulative distribution functions generated between the EC_{CRS} and the BEC_{VRS} in this study is not unexpected. As shown in equation (16) in section 2.3.3, the distance formulas that are used to develop the biennial efficiency (BEC_{VRS}) change and the traditional efficiency change under VRS are the same. Therefore, the differences between EC_{CRS} and the BEC_{VRS} in this analysis are due to the differences between the observations and the different efficiency frontiers (CRS and VRS respectively) in their represented years.

Finally, for 14 periods there is a statistically significant difference between TC_{CRS} and BTC_{VRS} when analyzing their empirical cumulative distribution functions. The periods where a statistical difference was not found were: 1997-1998; 1998-1999; 2003-2004; and 2009-2010. The T-test comparing if the means of the empirical cumulative distribution functions developed from the computed TC_{CRS} and BTC_{VRS} support that the means are different for the two samples of farms for 15 of the periods. For three of the periods (1993-1994; 1997-1998; and 2009-2010) the null hypothesis was not rejected. Corresponding with the KS-test results obtained, the T-tests indicate that bias is generally present when assuming CRS technology and VRS is the true technology.

The evidence in this sample supports a difference between evaluating the CRS and VRS using the MI_{CRS} and BMI_{VRS} techniques. Using the T-tests to evaluate bias (on-average), the means of the empirical cumulative distribution functions developed from the TC_{CRS} and BTC_{VRS} show the strongest support for bias if TC_{CRS} is selected.

Table 5.7 Summary Statistics of Kolmogorov-Smirnov Tests Comparing ecdf distributions for: MI-CRS and BMI-VRS; EC-CRS and BEC-VRS; and TC-CRS and BTC-VRS

Kolmogorov-Smirnov Test		1993-1994	1994-1995	1995-1996	1996-1997	1997-1998	1998-1999
MI-CRS : BMI-VRS	Test-Statistic	0.162	0.215	0.323	0.192	0.246	0.269
	P-Value	0.060	0.004	0.000	0.014	0.001	0.000
EC-CRS : BEC-VRS	Test-Statistic	0.108	0.115	0.108	0.131	0.100	0.177
	P-Value	0.411	0.333	0.417	0.201	0.513	0.030
TC-CRS : BTC-VRS	Test-Statistic	0.185	0.469	0.515	0.208	0.115	0.146
	P-Value	0.021	0.000	0.000	0.006	0.333	0.113

Two Sample T-test							
MI-CRS : BMI-VRS	Test-Statistic	0.534	-2.166	3.738	1.057	-0.519	2.777
	P-Value	0.594	0.031	0.000	0.291	0.604	0.006
EC-CRS : BEC-VRS	Test-Statistic	0.166	0.875	-0.104	1.617	0.360	-1.504
	P-Value	0.868	0.382	0.917	0.107	0.372	0.134
TC-CRS : BTC-VRS	Test-Statistic	0.435	-8.365	8.051	2.836	-0.624	-1.833
	P-Value	0.664	0.000	0.000	0.005	0.533	0.068

Table 5.7 Summary Statistics of Kolmogorov-Smirnov Tests Comparing ecdf distributions for: MI-CRS and BMI-VRS; EC-CRS and BEC-VRS; and TC-CRS and BTC-VRS (continued)

Kolmogorov-Smirnov Test		1999-2000	2000-2001	2001-2002	2002-2003	2003-2004	2004-2005
MI-CRS : BMI-VRS	Test-Statistic	0.192	0.208	0.317	0.154	0.292	0.123
	P-Value	0.014	0.006	0.043	0.083	0.000	0.261
EC-CRS : BEC-VRS	Test-Statistic	0.138	0.100	0.123	0.108	0.123	0.108
	P-Value	0.152	0.513	0.261	0.417	0.261	0.417
TC-CRS : BTC-VRS	Test-Statistic	0.169	0.231	0.192	0.262	0.146	0.323
	P-Value	0.043	0.002	0.014	0.000	0.113	0.000

Two Sample T-test							
MI-CRS : BMI-VRS	Test-Statistic	0.850	0.164	-0.201	1.579	3.412	1.382
	P-Value	0.396	0.870	0.841	0.115	0.001	0.168
EC-CRS : BEC-VRS	Test-Statistic	0.959	0.699	-0.198	0.999	-0.111	-0.303
	P-Value	0.338	0.485	0.843	0.319	0.911	0.762
TC-CRS : BTC-VRS	Test-Statistic	2.046	-4.276	-2.563	4.380	-2.399	5.090
	P-Value	0.042	0.000	0.011	0.000	0.017	0.000

Table 5.7 Summary Statistics of Kolmogorov-Smirnov Tests Comparing ecdf distributions for: MI-CRS and BMI-VRS; EC-CRS and BEC-VRS; and TC-CRS and BTC-VRS (continued)

Kolmogorov-Smirnov Test		2005-2006	2006-2007	2007-2008	2008-2009	2009-2010	2010-2011
MI-CRS : BMI-VRS	Test-Statistic	0.246	0.246	0.177	0.231	0.154	0.169
	P-Value	0.001	0.001	0.030	0.002	0.083	0.043
EC-CRS : BEC-VRS	Test-Statistic	0.177	0.200	0.115	0.146	0.131	0.115
	P-Value	0.030	0.009	0.333	0.113	0.201	0.333
TC-CRS : BTC-VRS	Test-Statistic	0.531	0.362	0.323	0.192	0.108	0.223
	P-Value	0.000	0.000	0.000	0.014	0.417	0.002

Two Sample T-test							
MI-CRS : BMI-VRS	Test-Statistic	-1.798	2.155	1.138	-0.242	0.759	-0.371
	P-Value	0.073	0.032	0.256	0.809	0.448	0.711
EC-CRS : BEC-VRS	Test-Statistic	0.903	-2.059	1.254	-0.199	0.185	0.919
	P-Value	0.367	0.040	0.211	0.843	0.854	0.359
TC-CRS : BTC-VRS	Test-Statistic	-8.741	5.394	4.086	-3.497	0.045	3.125
	P-Value	0.000	0.000	0.000	0.001	0.964	0.002

5.4 The impact of BES on Productivity assuming VRS

The empirical cumulative distribution function of BMI_{VRS}, BEC_{VRS}, and BTC_{VRS} was developed and compared using a Kolmogorov-Smirnov goodness-of-fit test (KS-test) for biotechnology enhanced soybean (BES) between adopters and non-adopters across the sample farms to examine the evidence of the impact from BES adoption. T-tests were then run to assess the differences (on average) between the empirical cumulative distribution function means that might be found. The results are summarized in Table 5.8.

We can only reject the null hypothesis that the empirical cumulative distribution functions between BES adopters and non-adopters were drawn from the same population at the 10% level of significance for 1 period (1997-1998) examining the BMI_{VRS}. Likewise, from testing the BTC_{VRS} empirical cumulative distribution functions between BES adopters and non-adopters, we can only reject at the 10% level of significance for the same period in this sample (1997-1998) that there is a statistical difference between the populations of BES adopters and non-adopters. There is no period in which we reject that the empirical cumulative distribution functions of BEC_{VRS} (distributions between adopters and non-adopters) are different.

The T-tests performed to examine the empirical cumulative distribution function means for BMI_{VRS}, BEC_{VRS}, and BTC_{VRS} only find support that the means are different between BES adopters and non-adopters in 1, 3, and 4 periods respectively. Given the KS-tests prior, we find strong evidence that the populations from which the BES adopters and non-adopters are drawn are not statistically different from each other. Thus we conclude that on-farm productivity, efficiency change, and technical change measures are not significantly impacted by the adoption or lack of adoption of BES. While this study found no gain or loss in efficiency from adopting

BES, it did not analyze any labor-savings from the adoption of BES that may have been available for other on-farm enterprises or off-farm employment.

Similar to Smith (2002) indicating that on-farm financial returns alone may not potentially account for increased off-farm employment available with time savings available following adoption of BES, there may well be increases in effort for other non-crop enterprises on the farm that are not accounted for with the crop inputs and outputs analyzed in this study. If the farm families represented in this study adopted BES and spent more time engaged in off-farm employment, there was no decrease in on-farm productivity or efficiency found in this analysis compared to those farms not adopting BES.

Table 5.8 Summary Statistics of Kolmogorov-Smirnov and T-Tests Comparing ecdf Distributions of BMI, BEC, and BTC For Adopters and Non-Adopters of BES

Kolmogorov-Smirnov Test		1995-1996	1996-1997	1997-1998	1998-1999	1999-2000	2000-2001
BMI Adopt : Non-Adopt	Test-Statistic	0.134	0.134	0.221	0.052	0.138	0.027
	P-Value	0.414	0.368	0.048	0.839	0.284	0.954
BEC: Adopt:Non-Adopt	Test-Statistic	0.175	0.077	0.096	0.096	0.123	0.013
	P-Value	0.225	0.721	0.561	0.551	0.365	0.988
BTC: Adopt:Non-Adopt	Test-Statistic	0.116	0.172	0.240	0.019	0.120	0.061
	P-Value	0.517	0.193	0.028	0.978	0.386	0.784

Two Sample T-test on Means							
BMI Adopt : Non-Adopt	Adopter Mean	1.222	1.019	0.960	1.038	0.925	1.134
	Non-Adopter Mean	1.282	1.041	0.962	1.009	0.999	1.058
	Test-Statistic	-1.025	-0.928	-0.360	0.432	-1.731	1.588
	P-Value	0.845	0.822	0.640	0.333	0.957	0.057
BEC: Adopt:Non-Adopt	Adopter Mean	0.993	1.033	1.001	0.941	0.948	1.160
	Non-Adopter Mean	1.047	1.035	1.006	0.959	1.004	1.111
	Test-Statistic	-1.479	-0.055	-0.169	-0.534	-1.184	1.333
	P-Value	0.928	0.522	0.567	0.703	0.880	0.092
BTC: Adopt:Non-Adopt	Adopter Mean	1.233	0.985	0.959	1.131	0.967	0.971
	Non-Adopter Mean	1.223	1.015	0.970	1.072	0.996	0.958
	Test-Statistic	0.176	-1.307	-0.479	1.638	-1.150	0.508
	P-Value	0.431	0.902	0.683	0.053	0.874	0.306

Table 5.8 Summary Statistics of Kolmogorov-Smirnov and T-Tests Comparing ecdf Distributions of BMI, BEC, and BTC For Adopters and Non-Adopters of BES (continued)

Kolmogorov-Smirnov Test		2001-2002	2002-2003	2003-2004	2004-2005	2005-2006	2006-2007
BMI Adopt : Non-Adopt	Test-Statistic	0.101	0.127	0.058	0.221	0.093	0.058
	P-Value	0.523	0.362	0.813	0.052	0.593	0.815
BEC: Adopt:Non-Adopt	Test-Statistic	0.109	0.104	0.128	0.140	0.070	0.023
	P-Value	0.472	0.503	0.365	0.309	0.745	0.968
BTC: Adopt:Non-Adopt	Test-Statistic	0.126	0.171	0.022	0.198	0.174	0.186
	P-Value	0.367	0.158	0.970	0.094	0.159	0.124

Two Sample T-test on Means							
BMI Adopt : Non-Adopt	Adopter Mean	0.908	1.114	1.144	1.029	0.931	1.104
	Non-Adopter Mean	0.919	1.165	1.146	1.079	0.956	1.046
	Test-Statistic	-0.246	-0.939	-0.032	-1.116	-0.555	0.913
	P-Value	0.597	0.825	0.513	0.864	0.710	0.182
BEC: Adopt:Non-Adopt	Adopter Mean	0.930	1.051	1.002	1.002	1.053	0.898
	Non-Adopter Mean	0.926	1.082	1.050	1.037	1.079	0.850
	Test-Statistic	0.380	-0.374	-0.990	-0.535	-0.265	1.497
	P-Value	0.352	0.645	0.838	0.703	0.604	0.069
BTC: Adopt:Non-Adopt	Adopter Mean	0.963	1.041	1.124	1.023	0.877	1.220
	Non-Adopter Mean	0.994	1.090	1.083	1.047	0.891	1.270
	Test-Statistic	-1.146	-1.587	1.087	-1.071	-0.554	-0.877
	P-Value	0.872	0.942	0.140	0.856	0.709	0.808

Table 5.8 Summary Statistics of Kolmogorov-Smirnov and T-Tests Comparing ecdf Distributions of BMI, BEC, and BTC For Adopters and Non-Adopters of BES (continued)

Kolmogorov-Smirnov Test		2007-2008	2008-2009	2009-2010	2010-2011
BMI Adopt : Non-Adopt	Test-Statistic	0.087	0.109	0.106	0.051
	P-Value	0.636	0.509	0.542	0.867
BEC: Adopt:Non-Adopt	Test-Statistic	0.100	0.112	0.065	0.084
	P-Value	0.549	0.494	0.796	0.678
BTC: Adopt:Non-Adopt	Test-Statistic	0.044	0.059	0.158	0.023
	P-Value	0.893	0.821	0.256	0.971

Two Sample T-test on Means					
BMI Adopt : Non-Adopt	Adopter Mean	1.235	1.027	0.972	1.017
	Non-Adopter Mean	1.275	1.050	1.013	0.944
	Test-Statistic	-0.387	-0.349	-0.579	1.233
	P-Value	0.650	0.636	0.717	0.111
BEC: Adopt:Non-Adopt	Adopter Mean	1.142	1.019	0.950	1.067
	Non-Adopter Mean	1.258	1.109	0.900	1.084
	Test-Statistic	-0.971	-1.380	1.423	-0.106
	P-Value	0.832	0.913	0.079	0.542
BTC: Adopt:Non-Adopt	Adopter Mean	1.072	0.999	1.015	0.951
	Non-Adopter Mean	1.022	0.942	1.128	0.875
	Test-Statistic	1.805	1.834	-1.902	1.918
	P-Value	0.037	0.036	0.968	0.030

Chapter 6 - Cost Effectiveness, Cost Efficiency, and Output Mix Efficiency Analysis of BES

Cost efficiency measures were estimated using input-oriented cost-minimization problems with 1) revenue constraints such that optimized input and outputs resulted in target revenues at least as large as observed in the sample; and separately 2) with output constraints that required farms to produce at least as much output at their observed levels, using GAMS. The first model (problem 17) was estimated to obtain results under the assumption of constant returns-to-scale (CRS) and the second (problem 19) assuming variable returns-to-scale (VRS). The results for problems (17) and (19) were respectively combined with the observed costs for the farms following equation (18) and (20) to measure cost-effectiveness or revenue-indirect cost efficiency (RICE) measures under CRS and VRS respectively.

The traditional cost-minimization problem given by problem (21) is constrained so that farms produce at least as much as their observed level of output and was solved using GAMS. The results were used in the relationship in equation (22) to measure efficiency for each farm in the sample. After solving problems (19) and (21) for each farm, output mix efficiency was estimated for each farm under variable returns-to-scale using equation (24).

Following a comparison of the cost-effectiveness measures under CRS and VRS, the estimations under VRS were analyzed to examine the impact of adopting biotechnology enhanced soybeans (BES) by the sample farms. Regression analysis was performed to estimate the impact of adopting BES on the cost-effectiveness, cost-efficiency, and output mix efficiency of the sample farms.

6.1 Cost Effectiveness under CRS and VRS

Under constant returns-to-scale (CRS), analysis of cost-effectiveness finds at most 2 fully efficient farms in 1994 and 1995 (Table 6.1). Every other year in the analysis finds only one fully efficient farm under CRS. Under CRS the potential for farms to reference one (or a few) farm(s) that appears to be more efficient than the others makes the overall analysis sensitive to potential data-entry, survey error, outliers limiting usefulness of comparisons, or to a farm that does not represent an appropriate crop enterprise mix given the resource or geographic constraints of the farms in the sample being examined. The fully-efficient farms in this analysis do not appear to be outliers upon examination of the data. This section is meant to highlight the dependence that the overall sample can have on returns to scale assumptions.

Table 6.1 Cost-Effectiveness Measures under CRS for a Sample of Kansas Farms

Summary Statistics		1993	1994	1995	1996	1997	1998
Revenue-Indirect	Mean	0.446	0.501	0.477	0.475	0.530	0.493
Cost Efficiency - CRS	Min	0.049	0.077	0.054	0.067	0.101	0.102
(RICE-CRS)	Max	1.000	1.000	1.000	1.000	1.000	1.000
	Std Dev	0.211	0.212	0.209	0.209	0.206	0.190
Distribution of Farms:							
RICE-CRS < 0.40		55	41	47	43	34	42
0.40≤ RICE-CRS < 0.50		28	21	21	30	20	24
0.50≤ RICE-CRS < 0.60		15	29	25	21	28	31
0.60≤ RICE-CRS < 0.70		12	12	14	11	20	11
0.70≤ RICE-CRS < 0.80		12	16	15	13	14	11
0.80≤ RICE-CRS < 0.90		4	6	2	10	9	8
0.90≤ RICE-CRS < 1.00		2	2	3	0	3	1
RICE-CRS = 1.00		1	2	2	1	1	1

Summary Statistics		1999	2000	2001	2002	2003	2004
Revenue-Indirect	Mean	0.325	0.315	0.441	0.452	0.430	0.385
Cost Efficiency - CRS	Min	0.049	0.050	0.104	0.093	0.085	0.098
	Max	1.000	1.000	1.000	1.000	1.000	1.000
	Std Dev	0.147	0.142	0.163	0.204	0.180	0.156
Distribution of Farms:							
RICE-CRS < 0.40		95	98	47	59	60	76
0.40≤ RICE-CRS < 0.50		22	20	32	27	30	25
0.50≤ RICE-CRS < 0.60		8	8	35	14	20	17
0.60≤ RICE-CRS < 0.70		2	1	7	13	9	7
0.70≤ RICE-CRS < 0.80		1	0	5	5	6	3
0.80≤ RICE-CRS < 0.90		0	1	2	8	2	0
0.90≤ RICE-CRS < 1.00		0	0	0	2	1	0
RICE-CRS = 1.00		1	1	1	1	1	1

Table 6.1 Cost-Effectiveness Measures under CRS for a Sample of Kansas Farms (continued)

Summary Statistics		2005	2006	2007	2008	2009	2010	2011
Revenue-Indirect	Mean	0.457	0.488	0.318	0.421	0.444	0.341	0.424
Cost Efficiency - CRS	Min	0.103	0.091	0.010	0.083	0.049	0.089	0.080
	Max	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Std Dev	0.170	0.175	0.153	0.169	0.160	0.144	0.185
Distribution of Farms:								
RICE-CRS < 0.40		42	40	94	64	49	95	59
0.40≤ RICE-CRS < 0.50		39	32	27	26	35	22	28
0.50≤ RICE-CRS < 0.60		25	22	3	24	29	6	20
0.60≤ RICE-CRS < 0.70		13	21	2	6	9	3	12
0.70≤ RICE-CRS < 0.80		6	8	1	6	4	0	7
0.80≤ RICE-CRS < 0.90		2	4	1	1	1	1	0
0.90≤ RICE-CRS < 1.00		1	1	0	1	1	1	2
RICE-CRS = 1.00		1	1	1	1	1	1	1

The cost-effectiveness measurements estimated for the sample assuming variable returns-to-scale (VRS) find 3 fully efficient farms in 1993 and 2011 (Table 6.2). Every other year has more farms on their efficient-frontier with the highest number of fully efficient farms being 9 in 1994. The mean level of inefficiency for farms in each year under VRS is consistently much closer to the level of the fully efficient farms than under CRS (Figure 6.1). We also find that at least the directional shifts in the cost effectiveness results under CRS and VRS are generally similar.

The assumption under the cost-effectiveness model that outputs can be varied so long as target revenue levels are achieved can be problematic in the analysis of farms across a state as diverse in geography, climate and resources as Kansas. The linkage to an efficient set with limited crop mix options may be problematic if you cannot find farms with similar crop mixes due to resource (environmental) constraints, which are often binding. This factor makes the large number of efficient farms under VRS more attractive for potentially finding an appropriate crop-type mix to compare more diverse farms. This diversity of production factors also lends support for assuming VRS as the true technology.

Table 6.2 Cost-Effectiveness Measures under VRS for a Sample of Kansas Farms

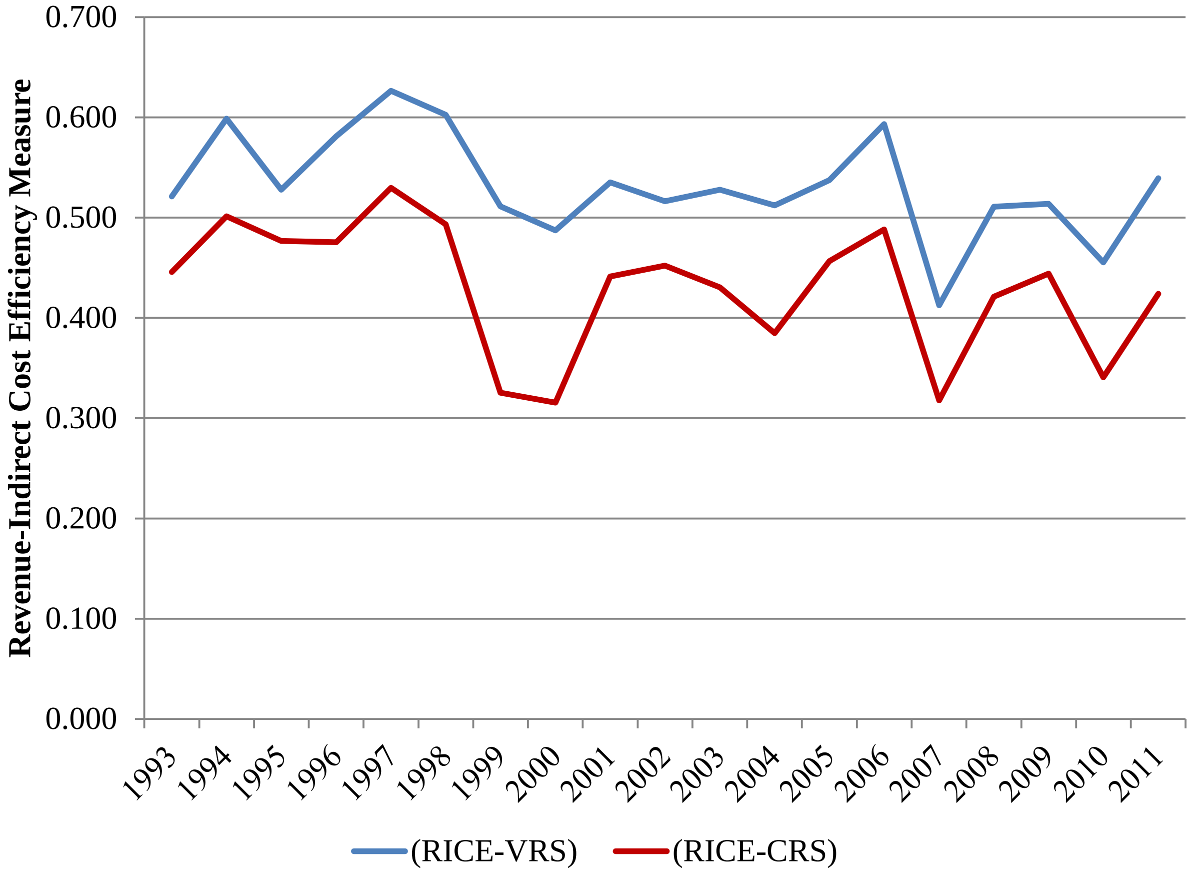
Summary Statistics		1993	1994	1995	1996	1997	1998
Revenue-Indirect	Mean	0.521	0.599	0.528	0.581	0.626	0.602
Cost Efficiency - VRS	Min	0.091	0.110	0.073	0.094	0.132	0.165
(RICE-VRS)	Max	1.000	1.000	1.000	1.000	1.000	1.000
	Std Dev	0.212	0.227	0.211	0.224	0.205	0.205
Distribution of Farms:							
RICE-VRS < 0.40		36	27	35	26	14	18
0.40≤ RICE-VRS < 0.50		26	14	22	22	20	23
0.50≤ RICE-VRS < 0.60		25	21	25	20	24	26
0.60≤ RICE-VRS < 0.70		14	20	21	26	23	23
0.70≤ RICE-VRS < 0.80		12	22	15	10	21	17
0.80≤ RICE-VRS < 0.90		10	12	4	11	15	9
0.90≤ RICE-VRS < 1.00		3	4	3	9	4	7
RICE-VRS = 1.00		3	9	4	5	8	6

Summary Statistics		1999	2000	2001	2002	2003	2004
Revenue-Indirect	Mean	0.511	0.487	0.535	0.516	0.528	0.512
Cost Efficiency - VRS	Min	0.122	0.100	0.122	0.137	0.091	0.120
	Max	1.000	1.000	1.000	1.000	1.000	1.000
	Std Dev	0.194	0.187	0.184	0.216	0.204	0.213
Distribution of Farms:							
RICE-VRS < 0.40		38	40	27	39	35	38
0.40≤ RICE-VRS < 0.50		23	30	21	28	26	34
0.50≤ RICE-VRS < 0.60		30	29	45	26	25	17
0.60≤ RICE-VRS < 0.70		21	17	17	10	22	16
0.70≤ RICE-VRS < 0.80		7	5	9	9	9	10
0.80≤ RICE-VRS < 0.90		4	3	2	8	2	5
0.90≤ RICE-VRS < 1.00		2	1	4	4	4	3
RICE-VRS = 1.00		4	4	4	5	6	6

Table 6.2 Cost-Effectiveness Measures under VRS for a Sample of Kansas Farms (continued)

Summary Statistics		2005	2006	2007	2008	2009	2010	2011
Revenue-Indirect	Mean	0.538	0.593	0.413	0.511	0.514	0.455	0.539
Cost Efficiency - VRS	Min	0.122	0.186	0.087	0.130	0.154	0.129	0.141
	Max	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Std Dev	0.195	0.191	0.184	0.194	0.191	0.188	0.203
Distribution of Farms:								
RICE-VRS < 0.40		31	19	70	34	36	57	29
0.40≤ RICE-VRS < 0.50		25	18	27	34	29	40	32
0.50≤ RICE-VRS < 0.60		32	28	19	29	32	12	24
0.60≤ RICE-VRS < 0.70		20	30	4	11	11	6	18
0.70≤ RICE-VRS < 0.80		7	18	3	9	10	5	12
0.80≤ RICE-VRS < 0.90		4	7	1	6	4	1	7
0.90≤ RICE-VRS < 1.00		5	2	0	0	1	3	4
RICE-VRS = 1.00		5	7	5	6	6	5	3

Figure 6.1 Distribution of Mean Cost-Effectiveness Measures under CRS and VRS for a Sample of Kansas Farms



6.2 Cost-Effectiveness Measures for BES Adopters and Non-Adopters

The summary of cost-effectiveness results under CRS for BES adopters and non-adopters are presented in Tables 6.3 and 6.4, respectively. The average cost-effectiveness measures under CRS are generally higher for BES adopters – but not consistently across the years examined. In 1998, 1999, 2000 and 2008 the average cost-effectiveness under CRS is higher for non-adopters than BES adopters. Toward the end of the analysis period, the adopter group tends to have more farms in the higher efficiency categories than the non-adopter group.

The summary of cost-effectiveness measures under VRS for BES adopters and non-adopters are presented in Tables 6.5 and 6.6, respectively. Unlike CRS, under VRS the BES non-adopter group is more efficient on average than the adopter group in this sample analysis. In 1996, 1997, 2001, 2009, and 2011, the adopter group is more efficient under VRS. The differences in the means between the adopter and non-adopter groups under CRS and VRS indicate a significant importance in making the correct technology assumption in the analysis implemented.

Regression analysis using the cost-effectiveness measurements obtained under CRS and VRS were run as proposed in section 2.2.2. A binary (0,1) variable [ADOPT] was used as a regressor where ADOPT equals 1 if the farm had adopted BES in period *t* or in a prior year of the analysis, and equal to 0 otherwise. The other independent variables in the linear regression analysis included a binary (0,1) dummy variable to account for statewide negative yield incidents between 1993 and 2011. The variables W95, W00, W02, W03, and W11 are yearly dummy variables equal to1 in 1995, 2000, 2002, 2003 and 2011, and 0 otherwise, respectively. These are the years when a statewide negative yield impact occurred with at least one of the primary crops (corn, soybeans, sorghum, or wheat), experiencing a statewide average yield per acre that was less than 80% of the preceding five-year moving average as reported by USDA-NASS (USDA-NASS, Quick Stats). A trend was also included in the regression, as well. The regression estimated was (following equation(30)):

(30) Cost-Effectiveness = $\beta_0 + \beta_1$ (ADOPT) + β_2 (W95) + β_3 (W00) + β_4 (W02) + β_5 (W03) + β_6 (W11) + β_7 (TREND) + U

A Tobit model was also run following the methods in section 4.3 as another method to check for robustness. The results of the linear regression and tobit analysis are presented in Table 6.7 for CRS and in Table 6.8 for VRS. The coefficient on the ADOPT variable was significant and positive at the 5% level – as was the marginal effect estimated in the Tobit model for cost-effectiveness under CRS. Thus adopting biotechnology enhanced soybeans would be expected to allow farms to be more efficient in minimizing costs while maintaining revenue levels in this study assuming constant returns-to-scale.

The coefficient on the ADOPT variable was <u>not</u> statistically significant at the 10% level – nor was the marginal effect that was estimated in the Tobit model for cost-effectiveness assuming variable returns-to-scale. Thus adopting biotechnology enhanced soybeans would not be expected to allow farms to be more efficient in minimizing costs while maintaining revenue levels in this study when assuming variable returns-to-scale.

Table 6.3 Cost-Effectiveness Measures under CRS for BES Adopters in a Sample of Kansas Farms

Summary Statistics		1993	1994	1995	1996	1997	1998
Revenue-Indirect	Mean				0.519	0.553	0.480
Cost Efficiency - CRS	Min				0.114	0.142	0.138
(RICE-CRS)	Max				0.875	0.970	1.000
BES Adopters	Std Dev				0.217	0.213	0.174
Distribution of Farms:							
RICE-CRS < 0.40					7	9	15
0.40≤ RICE-CRS < 0.50					9	4	12
0.50≤ RICE-CRS < 0.60					4	11	11
0.60≤ RICE-CRS < 0.70					1	3	2
0.70≤ RICE-CRS < 0.80					5	5	3
0.80≤ RICE-CRS < 0.90					4	3	2
0.90≤ RICE-CRS < 1.00					0	2	0
RICE-CRS = 1.00					0	0	1

Summary Statistics		1999	2000	2001	2002	2003	2004
Revenue-Indirect	Mean	0.318	0.314	0.462	0.461	0.436	0.393
Cost Efficiency - CRS	Min	0.087	0.086	0.107	0.133	0.085	0.102
(RICE-CRS)	Max	0.631	0.802	1.000	0.956	0.928	1.000
	Std Dev	0.121	0.136	0.174	0.202	0.183	0.165
Distribution of Farms:							
RICE-CRS < 0.40		40	56	25	37	37	46
0.40≤ RICE-CRS < 0.50		6	12	19	16	18	17
0.50≤ RICE-CRS < 0.60		3	4	19	8	12	12
0.60≤ RICE-CRS < 0.70		1	1	5	9	7	6
0.70≤ RICE-CRS < 0.80		0	0	4	4	4	2
0.80≤ RICE-CRS < 0.90		0	1	2	5	2	0
0.90≤ RICE-CRS < 1.00		0	0	0	2	1	0
RICE-CRS = 1.00		0	0	1	0	0	1

Table 6.3 Cost-Effectiveness Measures under CRS for BES Adopters in a Sample of Kansas Farms (continued)

Summary Statistics		2005	2006	2007	2008	2009	2010	2011
Revenue-Indirect	Mean	0.453	0.492	0.318	0.419	0.457	0.347	0.442
Cost Efficiency - CRS	Min	0.116	0.091	0.065	0.108	0.153	0.099	0.109
(RICE-CRS)	Max	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Std Dev	0.164	0.174	0.148	0.160	0.161	0.139	0.187
Distribution of Farms:								
RICE-CRS < 0.40		27	27	65	43	32	69	38
0.40≤ RICE-CRS < 0.50		29	22	18	21	25	15	22
0.50≤ RICE-CRS < 0.60		16	15	0	15	23	5	16
0.60≤ RICE-CRS < 0.70		8	12	1	3	6	2	8
0.70≤ RICE-CRS < 0.80		4	6	0	3	2	0	6
0.80≤ RICE-CRS < 0.90		1	2	1	0	1	1	0
0.90≤ RICE-CRS < 1.00		0	1	0	1	1	0	2
RICE-CRS = 1.00		1	1	1	1	1	1	1

Table 6.4 Cost-Effectiveness Measures under CRS for BES Non-Adopters in a Sample of Kansas Farms

Summary Statistics		1993	1994	1995	1996	1997	1998
Revenue-Indirect	Mean				0.462	0.520	0.501
Cost Efficiency - CRS	Min				0.067	0.101	0.102
(RICE-CRS)	Max				1.000	1.000	0.999
BES Non-Adopters	Std Dev				0.205	0.203	0.199
Distribution of Farms:							
RICE-CRS < 0.40					36	25	27
0.40≤ RICE-CRS < 0.50					21	16	12
0.50≤ RICE-CRS < 0.60					17	17	20
0.60≤ RICE-CRS < 0.70					10	17	9
0.70≤ RICE-CRS < 0.80					8	9	8
0.80≤ RICE-CRS < 0.90					6	6	6
0.90≤ RICE-CRS < 1.00					0	1	1
RICE-CRS = 1.00					1	1	0

Summary Statistics		1999	2000	2001	2002	2003	2004
Revenue-Indirect	Mean	0.330	0.317	0.412	0.437	0.420	0.369
Cost Efficiency - CRS	Min	0.049	0.050	0.104	0.093	0.110	0.098
	Max	1.000	1.000	0.752	1.000	1.000	0.723
	Std Dev	0.162	0.151	0.143	0.210	0.176	0.139
Distribution of Farms:							
RICE-CRS < 0.40		55	42	22	22	23	30
0.40≤ RICE-CRS < 0.50		16	8	13	11	12	8
0.50≤ RICE-CRS < 0.60		5	4	16	6	8	5
0.60≤ RICE-CRS < 0.70		1	0	2	4	2	1
0.70≤ RICE-CRS < 0.80		1	0	1	1	2	1
0.80≤ RICE-CRS < 0.90		0	0	0	3	0	0
0.90≤ RICE-CRS < 1.00		0	0	0	0	0	0
RICE-CRS = 1.00		1	1	0	1	1	0

Table 6.4 Cost-Effectiveness Measures under CRS for BES Non-Adopters in a Sample of Kansas Farms (Continued)

Summary Statistics		2005	2006	2007	2008	2009	2010	2011
Revenue-Indirect	Mean	0.464	0.481	0.317	0.425	0.414	0.324	0.378
Cost Efficiency - CRS	Min	0.103	0.129	0.010	0.083	0.049	0.089	0.080
	Max	0.939	0.820	0.722	0.877	0.709	0.908	0.758
	Std Dev	0.183	0.179	0.164	0.190	0.156	0.156	0.173
Distribution of Farms:								
RICE-CRS < 0.40		15	13	29	21	17	26	21
0.40≤ RICE-CRS < 0.50		10	10	9	5	10	7	6
0.50≤ RICE-CRS < 0.60		9	7	3	9	6	1	4
0.60≤ RICE-CRS < 0.70		5	9	1	3	3	1	4
0.70≤ RICE-CRS < 0.80		2	2	1	3	2	0	1
0.80≤ RICE-CRS < 0.90		1	2	0	1	0	0	0
0.90≤ RICE-CRS < 1.00		1	0	0	0	0	1	0
RICE-CRS = 1.00		0	0	0	0	0	0	0

Table 6.5 Cost-Effectiveness Measures under VRS for BES Adopters in a Sample of Kansas Farms

Summary Statistics		1993	1994	1995	1996	1997	1998
Revenue-Indirect	Mean				0.594	0.639	0.570
Cost Efficiency - VRS	Min				0.166	0.200	0.169
(RICE-VRS)	Max				1.000	1.000	1.000
BES Adopters	Std Dev				0.229	0.217	0.176
Distribution of Farms:							
RICE-VRS < 0.40					5	5	5
0.40≤ RICE-VRS < 0.50					7	4	7
0.50≤ RICE-VRS < 0.60					4	7	18
0.60≤ RICE-VRS < 0.70					4	4	7
0.70≤ RICE-VRS < 0.80					2	9	5
0.80≤ RICE-VRS < 0.90					5	3	2
0.90≤ RICE-VRS < 1.00					2	2	0
RICE-VRS = 1.00					1	3	2

Summary Statistics		1999	2000	2001	2002	2003	2004
Revenue-Indirect	Mean	0.481	0.482	0.543	0.514	0.516	0.508
Cost Efficiency - VRS	Min	0.127	0.100	0.133	0.138	0.091	0.120
(RICE-VRS)	Max	0.847	1.000	1.000	1.000	1.000	1.000
BES Adopters	Std Dev	0.163	0.186	0.184	0.216	0.195	0.212
Distribution of Farms:							
RICE-VRS < 0.40		17	25	15	25	24	26
0.40≤ RICE-VRS < 0.50		11	17	15	16	15	22
0.50≤ RICE-VRS < 0.60		10	16	20	18	19	12
0.60≤ RICE-VRS < 0.70		9	10	12	5	10	9
0.70≤ RICE-VRS < 0.80		0	1	8	6	6	5
0.80≤ RICE-VRS < 0.90		3	2	0	5	2	4
0.90≤ RICE-VRS < 1.00		0	1	2	3	3	3
RICE-VRS = 1.00		0	2	3	3	2	3

Table 6.5 Cost-Effectiveness Measures under VRS for BES Adopters in a Sample of Kansas Farms (continued)

Summary Statistics		2005	2006	2007	2008	2009	2010	2011
Revenue-Indirect	Mean	0.515	0.577	0.401	0.495	0.518	0.453	0.544
Cost Efficiency - VRS	Min	0.122	0.189	0.091	0.130	0.154	0.129	0.141
(RICE-VRS)	Max	1.000	1.000	1.000	1.000	1.000	1.000	1.000
BES Adopters	Std Dev	0.185	0.176	0.178	0.185	0.198	0.185	0.205
Distribution of Farms:								
RICE-VRS < 0.40		22	13	49	24	25	41	20
0.40≤ RICE-VRS < 0.50		20	14	19	25	19	30	22
0.50≤ RICE-VRS < 0.60		22	18	13	19	25	9	17
0.60≤ RICE-VRS < 0.70		12	22	0	8	9	3	15
0.70≤ RICE-VRS < 0.80		4	12	1	4	5	4	9
0.80≤ RICE-VRS < 0.90		1	3	0	3	1	1	4
0.90≤ RICE-VRS < 1.00		1	1	0	0	1	1	3
RICE-VRS = 1.00		4	3	4	4	6	4	3

Table 6.6 Cost-Effectiveness Measures under VRS for BES Non-Adopters in a Sample of Kansas Farms

Summary Statistics		1993	1994	1995	1996	1997	1998
Revenue-Indirect	Mean				0.577	0.621	0.621
Cost Efficiency - VRS	Min				0.094	0.132	0.165
(RICE-VRS)	Max				1.000	1.000	1.000
BES Non-Adopters	Std Dev				0.223	0.201	0.218
Distribution of Farms:							
RICE-VRS < 0.40					21	9	13
0.40≤ RICE-VRS < 0.50					15	16	16
0.50≤ RICE-VRS < 0.60					16	17	8
0.60≤ RICE-VRS < 0.70					22	19	16
0.70≤ RICE-VRS < 0.80					8	12	12
0.80≤ RICE-VRS < 0.90					6	12	7
0.90≤ RICE-VRS < 1.00					7	2	7
RICE-VRS = 1.00					4	5	4

Summary Statistics		1999	2000	2001	2002	2003	2004
Revenue-Indirect	Mean	0.530	0.495	0.524	0.520	0.548	0.521
Cost Efficiency - VRS	Min	0.122	0.109	0.122	0.137	0.148	0.135
(RICE-VRS)	Max	1.000	1.000	1.000	1.000	1.000	1.000
BES Non-Adopters	Std Dev	0.210	0.191	0.184	0.218	0.219	0.218
Distribution of Farms:							
RICE-VRS < 0.40		21	15	12	14	11	12
0.40≤ RICE-VRS < 0.50		12	13	6	12	11	12
0.50≤ RICE-VRS < 0.60		20	13	25	8	6	5
0.60≤ RICE-VRS < 0.70		12	7	5	5	12	7
0.70≤ RICE-VRS < 0.80		7	4	1	3	3	5
0.80≤ RICE-VRS < 0.90		1	1	2	3	0	1
0.90≤ RICE-VRS < 1.00		2	0	2	1	1	0
RICE-VRS = 1.00		4	2	1	2	4	3

Table 6.6 Cost-Effectiveness Measures under VRS for BES Non-Adopters in a Sample of Kansas Farms (continued)

Summary Statistics		2005	2006	2007	2008	2009	2010	2011
Revenue-Indirect	Mean	0.583	0.627	0.436	0.545	0.504	0.461	0.527
Cost Efficiency - VRS	Min	0.170	0.186	0.087	0.144	0.160	0.143	0.161
(RICE-VRS)	Max	1.000	1.000	1.000	1.000	0.873	1.000	0.992
BES Non-Adopters	Std Dev	0.210	0.216	0.196	0.210	0.175	0.198	0.201
Distribution of Farms:								
RICE-VRS < 0.40		9	6	21	10	11	16	9
0.40≤ RICE-VRS < 0.50		5	4	8	9	10	10	10
0.50≤ RICE-VRS < 0.60		10	10	6	10	7	3	7
0.60≤ RICE-VRS < 0.70		8	8	4	3	2	3	3
0.70≤ RICE-VRS < 0.80		3	6	2	5	5	1	3
0.80≤ RICE-VRS < 0.90		3	4	1	3	3	0	3
0.90≤ RICE-VRS < 1.00		4	1	0	0	0	2	1
RICE-VRS = 1.00		1	4	1	2	0	1	0

Table 6.7 Tobit Regression Results for Cost-Effectiveness, Marginal Effects, BES Adoption, Negative Yield Events, and Time Assuming CRS

Independent Variable	RICE - CRS	Marginal Effects Tobit
Intercept	0.488***	
	(0.010)	
Adoption of BES	0.017**	0.017**
	(0.009)	(0.009)
Negative Yield Event 1995	0.008	0.008
	(0.018)	(0.018)
Negative Yield Event 2000	-0.132***	-0.131***
	(0.017)	(0.017)
Negative Yield Event 2002	0.016	0.016
	(0.017)	(0.017)
Negative Yield Event 2003	0.001	0.001
	(0.017)	(0.017)
Negative Yield Event 2011	0.044**	0.044**
	(0.018)	(0.018)
Trend	-0.006***	-0.006***
	(0.001)	(.001)

Note: Standard errors are in parentheses. Single, double, and triple asterisks (*) denote significance at the 10%, 5%, and 1% level, respectively.

Table 6.8 Tobit Regression Results for Cost-Effectiveness, Marginal Effects, BES Adoption, Negative Yield Events, and Time Assuming VRS

Independent Variable	RICE - VRS	Marginal Effects Tobit
Intercept	0.602***	
	(0.010)	
Adoption of BES	-0.016	-0.015
	(0.010)	(0.010)
Negative Yield Event 1995	-0.055***	-0.054***
	(0.021)	(0.020)
Negative Yield Event 2000	-0.060***	-0.058***
	(0.020)	(0.019)
Negative Yield Event 2002	-0.018	-0.018
	(0.020)	(0.019)
Negative Yield Event 2003	-0.000	-0.000
	(0.020)	(0.019)
Negative Yield Event 2011	0.055***	0.054***
	(0.021)	(0.021)
Trend	-0.006***	-0.005***
	(0.001)	(.001)

Note: Standard errors are in parentheses. Single, double, and triple asterisks (*) denote significance at the 10%, 5%, and 1% level, respectively.

6.3 Cost-Efficiency Measures for BES Adopters and Non-Adopters

The cost-efficiency measures for biotechnology enhanced soybean adopters and non-adopters are summarized in Tables 6.9 and 6.10 respectively. Only in 2006 and 2008 is the mean for the biotechnology enhanced soybean adopters cost-efficiency score higher than the mean of the cost-efficiency score of the non-adopters. This analysis of the means indicates that the BES non-adopter group is closer to the minimum level of costs estimated from the optimal input levels to produce the same level of outputs as observed in this analysis.

Table 6.11 provides the results of the Tobit regression analyses for the cost-efficiency measures of the farms assuming variable returns-to-scale. Adoption of biotechnology enhanced soybeans was not found to be statistically significant at a 10% level of significance. This lack of statistical significance leads us to find no evidence when assuming VRS that there is an impact on cost-efficiency measures (lower expenses for producing the same level of outputs) between adopters and non-adopters of BES.

Table 6.9 Cost-Efficiency Measures under VRS for BES Adopters in a Sample of Kansas Farms

Summary Statistics		1993	1994	1995	1996	1997	1998
Cost-Efficiency (VRS)	Mean				0.689	0.714	0.706
CE-VRS	Min				0.179	0.240	0.252
BES Adopters	Max				1.000	1.000	1.000
	Std Dev				0.243	0.229	0.213
Distribution of Farms:							
CE-VRS < 0.40					3	5	3
0.40≤ CE-VRS < 0.50					4	1	4
0.50≤ CE-VRS < 0.60					2	5	4
0.60≤ CE-VRS < 0.70					6	6	11
0.70≤ CE-VRS < 0.80					4	3	10
0.80≤ CE-VRS < 0.90					2	7	1
0.90≤ CE-VRS < 1.00					3	3	4
CE-VRS = 1.00					5	6	8

Summary Statistics		1999	2000	2001	2002	2003	2004
Cost-Efficiency (VRS)	Mean	0.666	0.632	0.761	0.661	0.690	0.677
CE-VRS	Min	0.242	0.134	0.235	0.184	0.170	0.181
BES Adopters	Max	1.000	1.000	1.000	1.000	1.000	1.000
	Std Dev	0.221	0.236	0.228	0.247	0.234	0.230
Distribution of Farms:							
CE-VRS < 0.40		6	14	5	13	8	12
0.40≤ CE-VRS < 0.50		8	9	8	14	9	11
0.50≤ CE-VRS < 0.60		5	12	5	10	15	9
0.60≤ CE-VRS < 0.70		8	8	9	11	11	15
0.70≤ CE-VRS < 0.80		8	13	14	6	7	12
0.80≤ CE-VRS < 0.90		4	6	4	8	8	5
0.90≤ CE-VRS < 1.00		3	3	11	2	8	5
CE-VRS = 1.00		7	9	19	17	15	15

Table 6.9 Cost-Efficiency Measures under VRS for BES Adopters in a Sample of Kansas Farms (continued)

Summary Statistics		2005	2006	2007	2008	2009	2010	2011
Cost-Efficiency (VRS)	Mean	0.713	0.755	0.653	0.748	0.739	0.639	0.725
CE-VRS	Min	0.161	0.259	0.143	0.286	0.231	0.279	0.180
BES Adopters	Max	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Std Dev	0.234	0.210	0.236	0.217	0.223	0.226	0.222
Distribution of Farms:								
CE-VRS < 0.40		7	3	13	6	10	12	7
0.40≤ CE-VRS < 0.50		10	7	10	9	6	15	11
0.50≤ CE-VRS < 0.60		12	13	15	7	12	22	10
0.60≤ CE-VRS < 0.70		14	11	16	17	12	14	17
0.70≤ CE-VRS < 0.80		11	11	5	7	11	7	10
0.80≤ CE-VRS < 0.90		4	13	8	11	11	2	10
0.90≤ CE-VRS < 1.00		6	9	4	10	3	3	9
CE-VRS = 1.00		22	19	15	20	26	18	19

Table 6.10 Cost-Efficiency Measures under VRS for BES Non-Adopters in a Sample of Kansas Farms

Summary Statistics		1993	1994	1995	1996	1997	1998
Cost-Efficiency (VRS)	Mean				0.721	0.786	0.778
CE-VRS	Min				0.129	0.157	0.221
BES Non-Adopters	Max				1.000	1.000	1.000
	Std Dev				0.248	0.223	0.217
Distribution of Farms:							
CE-VRS < 0.40					15	6	6
0.40≤ CE-VRS < 0.50					4	4	4
0.50≤ CE-VRS < 0.60					11	12	6
0.60≤ CE-VRS < 0.70					10	6	12
0.70≤ CE-VRS < 0.80					19	13	10
0.80≤ CE-VRS < 0.90					9	13	15
0.90≤ CE-VRS < 1.00					7	12	9
CE-VRS = 1.00					25	27	22

Summary Statistics		1999	2000	2001	2002	2003	2004
Cost-Efficiency (VRS)	Mean	0.742	0.709	0.770	0.681	0.741	0.714
CE-VRS	Min	0.156	0.149	0.214	0.178	0.165	0.198
BES Non-Adopters	Max	1.000	1.000	1.000	1.000	1.000	1.000
	Std Dev	0.241	0.226	0.221	0.247	0.228	0.234
Distribution of Farms:							
CE-VRS < 0.40		9	4	5	5	5	6
0.40≤ CE-VRS < 0.50		3	4	0	8	1	0
0.50≤ CE-VRS < 0.60		7	9	4	4	5	10
0.60≤ CE-VRS < 0.70		11	9	10	11	8	6
0.70≤ CE-VRS < 0.80		13	8	8	4	8	7
0.80≤ CE-VRS < 0.90		9	9	7	3	8	2
0.90≤ CE-VRS < 1.00		9	1	8	2	1	3
CE-VRS = 1.00		19	11	12	11	12	11

Table 6.10 Cost-Efficiency Measures under VRS for BES Non-Adopters in a Sample of Kansas Farms (continued)

Summary Statistics		2005	2006	2007	2008	2009	2010	2011
Cost-Efficiency (VRS)	Mean	0.761	0.749	0.672	0.743	0.740	0.671	0.737
CE-VRS	Min	0.178	0.211	0.143	0.197	0.229	0.180	0.168
BES Non-Adopters	Max	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Std Dev	0.241	0.233	0.268	0.234	0.237	0.253	0.256
Distribution of Farms:								
CE-VRS < 0.40		5	5	8	5	4	3	5
0.40≤ CE-VRS < 0.50		1	0	2	2	3	8	0
0.50≤ CE-VRS < 0.60		4	4	9	4	2	5	4
0.60≤ CE-VRS < 0.70		5	8	4	6	8	5	6
0.70≤ CE-VRS < 0.80		6	7	4	7	4	4	5
0.80≤ CE-VRS < 0.90		6	3	3	4	2	0	2
0.90≤ CE-VRS < 1.00		2	5	4	3	6	3	5
CE-VRS = 1.00		14	11	9	11	9	8	9

Table 6.11 Tobit Regression Results for Cost-Efficiency, Marginal Effects, BES Adoption, Negative Yield Events, and Time Assuming VRS

Independent Variable	Cost-Efficiency - VRS	Marginal Effects Tobit
Intercept	0.772***	
	(0.015)	
Adoption of BES	-0.005	-0.004
	(0.014)	(0.011)
Negative Yield Event 1995	-0.034	-0.027
	(0.029)	(0.023)
Negative Yield Event 2000	-0.072***	-0.057***
	(0.027)	(0.022)
Negative Yield Event 2002	-0.056**	-0.045**
	(0.027)	(0.022)
Negative Yield Event 2003	-0.013	-0.011
	(0.028)	(0.022)
Negative Yield Event 2011	0.017	0.014
	(0.030)	(0.024)
Trend	-0.001	-0.001
	(0.001)	(.001)

Note: Standard errors are in parentheses. Single, double, and triple asterisks (*) denote significance at the 10%, 5%, and 1% level, respectively.

6.4 Output Mix Efficiency Measures for BES Adopters and Non-Adopters

Table 6.12 summarizes the output mix efficiency results under variable returns-to-scale for adopters of biotechnology enhanced soybeans. Table 6.13 summarizes the output mix efficiency results for the non-adopters of biotechnology enhanced soybeans. In only four years (1996, 2004, 2009, and 2011) were the mean output mix efficiency scores for biotechnology enhanced soybean adopters higher than the mean found for the non-adopters.

Table 6.14 summarizes the Tobit model results for the output mix efficiency analysis. For output mix efficiency, the estimated impact of adopting biotechnology enhanced soybeans was negative and statistically significant at the 1% level. These results would indicate that there are more potential savings for non-adopters adjusting their output mix after other inefficiencies would be addressed than would be available for biotechnology enhanced soybean adopters.

Recall that the output mix efficiency is equal to the ratio of the solution to the cost-effectiveness problem (19) to the solution of the cost-efficiency problem (21). A lower output mix efficiency measure would indicate that the result of the cost-effectiveness problem is relatively smaller compared to the solution for the cost-efficiency problem for the farm than for a farm with a higher mix efficiency measure. The result would be a greater-amount of reduction in overall costs available through altering the crop mix of the farm with the lower output mix efficiency measure – in this case for the non-adopters of biotechnology enhanced soybeans. Another way to look at this result is that adopters of biotechnology enhanced soybeans are estimated to be closer to their optimum output mix than non-adopters when considering cost-minimization.

Table 6.12 Output Mix Efficiency Measures Under VRS for BES Adopters in a Sample of Kansas Farms

Summary Statistics		1993	1994	1995	1996	1997	1998
Output Mix Efficiency (VRS)	Mean				0.823	0.816	0.768
OME-VRS	Min				0.585	0.545	0.432
BES Adopters	Max				1.000	1.000	1.000
	Std Dev				0.113	0.109	0.123
Distribution of Farms:							
OME-VRS < 0.40					0	0	0
0.40≤ OME-VRS < 0.50					0	0	1
0.50≤ OME-VRS < 0.60					3	3	4
0.60≤ OME-VRS < 0.70					1	3	5
0.70≤ OME-VRS < 0.80					4	7	15
0.80≤ OME-VRS < 0.90					14	16	14
0.90≤ OME-VRS < 1.00					5	6	4
OME-VRS = 1.00					2	1	2

Summary Statistics		1999	2000	2001	2002	2003	2004
Output Mix Efficiency (VRS)	Mean	0.684	0.727	0.686	0.758	0.734	0.744
OME-VRS	Min	0.309	0.430	0.250	0.290	0.238	0.255
BES Adopters	Max	0.942	1.000	1.000	1.000	1.000	1.000
	Std Dev	0.140	0.141	0.120	0.130	0.127	0.144
Distribution of Farms:							
OME-VRS < 0.40		3	0	1	1	2	2
0.40≤ OME-VRS < 0.50		0	3	3	1	0	5
0.50≤ OME-VRS < 0.60		8	13	10	5	6	6
0.60≤ OME-VRS < 0.70		16	16	26	18	18	14
0.70≤ OME-VRS < 0.80		10	13	25	25	32	21
0.80≤ OME-VRS < 0.90		11	24	6	21	14	28
0.90≤ OME-VRS < 1.00		1	4	3	8	7	5
OME-VRS = 1.00		0	1	1	2	2	3

Table 6.12 Output Mix Efficiency Measures Under VRS for BES Adopters in a Sample of Kansas Farms (continued)

Summary Statistics		2005	2006	2007	2008	2009	2010	2011
Output Mix Efficiency (VRS)	Mean	0.737	0.776	0.623	0.667	0.706	0.716	0.761
OME-VRS	Min	0.259	0.363	0.257	0.247	0.415	0.361	0.178
BES Adopters	Max	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Std Dev	0.145	0.115	0.154	0.157	0.148	0.141	0.134
Distribution of Farms:								
OME-VRS < 0.40		1	1	3	3	0	3	1
0.40≤ OME-VRS < 0.50		3	0	19	8	8	6	1
0.50≤ OME-VRS < 0.60		12	6	18	20	16	8	4
0.60≤ OME-VRS < 0.70		18	16	18	23	17	17	22
0.70≤ OME-VRS < 0.80		16	23	16	16	26	37	27
0.80≤ OME-VRS < 0.90		26	35	9	9	16	15	24
0.90≤ OME-VRS < 1.00		7	2	0	5	2	3	11
OME-VRS = 1.00		3	3	3	3	6	4	3

Table 6.13 Output Mix Efficiency Measures Under VRS for BES Non-Adopters in a Sample of Kansas Farms

Summary Statistics		1993	1994	1995	1996	1997	1998
Output Mix Efficiency (VRS)	Mean				0.808	0.822	0.815
OME-VRS	Min				0.483	0.471	0.517
BES Non-Adopters	Max				1.000	1.000	1.000
	Std Dev				0.107	0.117	0.117
Distribution of Farms:							
OME-VRS < 0.40					0	0	0
0.40≤ OME-VRS < 0.50					1	2	0
0.50≤ OME-VRS < 0.60					3	3	4
0.60≤ OME-VRS < 0.70					8	8	9
0.70≤ OME-VRS < 0.80					32	19	26
0.80≤ OME-VRS < 0.90					37	37	19
0.90≤ OME-VRS < 1.00					16	17	22
OME-VRS = 1.00					3	7	4

Summary Statistics		1999	2000	2001	2002	2003	2004
Output Mix Efficiency (VRS)	Mean	0.759	0.763	0.732	0.795	0.764	0.729
OME-VRS	Min	0.256	0.532	0.485	0.549	0.432	0.403
BES Non-Adopters	Max	1.000	1.000	1.000	1.000	1.000	1.000
	Std Dev	0.161	0.124	0.136	0.114	0.128	0.144
Distribution of Farms:							
OME-VRS < 0.40		2	0	0	0	0	0
0.40≤ OME-VRS < 0.50		2	0	2	0	1	3
0.50≤ OME-VRS < 0.60		6	6	10	2	3	4
0.60≤ OME-VRS < 0.70		16	12	12	9	11	11
0.70≤ OME-VRS < 0.80		19	17	13	17	16	15
0.80≤ OME-VRS < 0.90		21	13	10	10	11	7
0.90≤ OME-VRS < 1.00		10	3	3	6	2	2
OME-VRS = 1.00		4	4	4	4	4	3

Table 6.13 Output Mix Efficiency Measures Under VRS for BES Non-Adopters in a Sample of Kansas Farms (continued)

Summary Statistics		2005	2006	2007	2008	2009	2010	2011
Output Mix Efficiency (VRS)	Mean	0.777	0.828	0.671	0.740	0.690	0.719	0.705
OME-VRS	Min	0.419	0.454	0.446	0.342	0.435	0.335	0.367
BES Non-Adopters	Max	1.000	1.000	1.000	1.000	1.000	1.000	0.999
	Std Dev	0.147	0.121	0.152	0.147	0.148	0.167	0.147
Distribution of Farms:								
OME-VRS < 0.40		0	0	0	1	0	1	1
0.40≤ OME-VRS < 0.50		2	1	6	1	5	2	1
0.50≤ OME-VRS < 0.60		4	1	9	4	7	5	7
0.60≤ OME-VRS < 0.70		8	6	12	10	6	4	10
0.70≤ OME-VRS < 0.80		8	4	7	12	11	15	8
0.80≤ OME-VRS < 0.90		12	21	5	9	6	4	6
0.90≤ OME-VRS < 1.00		7	6	2	2	2	3	3
OME-VRS = 1.00		2	4	2	3	1	2	0

Table 6.14 Tobit Regression Results for Output Mix Efficiency, Marginal Effects, BES Adoption, Negative Yield Events, and Time Assuming VRS

Independent Variable	Output Mix Efficiency - VRS	Marginal Effects Tobit
Intercept	0.825***	
	(0.007)	
Adoption of BES	-0.021***	-0.020***
	(0.007)	(0.006)
Negative Yield Event 1995	-0.040***	-0.039***
	(0.014)	(0.013)
Negative Yield Event 2000	-0.018	-0.017
	(0.013)	(0.013)
Negative Yield Event 2002	0.026*	0.024*
	(0.013)	(0.013)
Negative Yield Event 2003	0.005	0.005
	(0.013)	(0.013)
Negative Yield Event 2011	0.056***	0.053***
	(0.014)	(0.014)
Trend	-0.006***	-0.006***
	(0.001)	(.001)

Note: Standard errors are in parentheses. Single, double, and triple asterisks (*) denote significance at the 10%, 5%, and 1% level, respectively.

Chapter 7 - Conclusions, Policy Implications and Suggestions for Future Work

This study established a framework for analyzing on-farm efficiency impacts of adopting technology over time. Incorporating a panel data analysis with information on the adoption of biotechnology enhanced soybeans allowed for a non-parametric approach to estimate technical efficiency, cost-effectiveness, traditional cost-efficiency, output mix efficiency, and Malmquist productivity indexes for 129 farms in Kansas using data from 1993 through 2011. We compared the assumptions of constant returns-to-scale to variable returns-to-scale analyzing the differences found in the analysis from the different technology assumptions in this study.

This study found that the adoption of biotechnology enhanced soybeans increased the on-farm efficiency of the production of crops with the inputs and outputs considered. This was found for estimates of technical efficiency under variable returns-to-scale and for the ability of those farms to minimize costs while maintaining a target-level of revenue estimated with cost-effectiveness or revenue-indirect cost efficiency measures under constant returns-to-scale for the farms. The technical efficiency analysis under variable returns-to-scale indicated that overall production of crop outputs would be expected to be 1.7% higher for adopters of biotechnology enhanced soybeans than for similar farms that did not adopt biotechnology enhanced soybeans.

While no significant differences in the Malmquist productivity indices or its decompositions into technical change and efficiency change were found between adopters of biotechnology enhanced soybeans (BES) and those without adoption experience, we find strong support for on-farm efficiency gains in the other portions of this analysis.

The impacts of assuming constant returns-to-scale vs. variable returns-to-scale in the estimation of efficiency measures was shown to be statistically significant under most of the techniques used in this study. This finding emphasizes the need for appropriate selection of returns-to-scale in analyses of efficiency and productivity changes so that results are not biased. The biennial Malmquist productivity index was used to develop estimates of productivity change along with its decompositions into efficiency change and technical change, avoiding numerical infeasibilities that often arise when considering variable returns-to-scale technologies when they may be the true underlying technology.

7.1 Considering On-Farm Efficiency Analysis for BES and Off-Farm Efficiency

This study examined only crop outputs in the analyses. It is possible that any simplification of the management systems from the adoption of herbicide-tolerant BES may be able to increase time available for: expanding crop acres farmed, management of non-crop enterprises for farms, or increasing off-farm employment. For example, livestock enterprises may benefit from any realized time available from reduced labor required for crop enterprises.

Fernandez-Cornejo (2007) found that "Higher off-farm income is significantly related to the adoption of technologies that economize on management time (management saving such as herbicide-tolerant crops, conservation tillage) (p. iv)." Time savings for existing production enterprises, could also be used to expand the farm size or scope – potentially enhancing diversification or profit opportunities. The on-farm efficiency gains attributed to BES adoption here, supports the greater overall return to farm-family income while allowing for other advantages of the simplified weed management program that is implemented with BES.

7.2 The Implications of Herbicide-Resistance in Weeds

The simplification of the management system for controlling weed-pressure in soybeans is cited in Fernandez-Cornejo (2007) and Fernandez-Cornejo and Caswell (2006). This study finds that there is not generally a decrease in efficiency for the production of crops when BES was adopted in the management systems for the sample of Kansas farms analyzed. If the weeds that have been controlled prior by the BES systems – or new weeds – become uncontrolled beyond economic thresholds, they would be expected to reduce the efficiency of crop production for these farms without other off-setting changes by through reductions in crop production. Bradley et al. (2009) define the economic threshold for weeds as "the density of a weed population at which control is economically justified. Control may be economically justified if there is potential for yield loss, crop quality loss, harvesting difficulties, aesthetic issues or future weed management difficulties due to weed seed production."

The framework of this study may be of use in evaluating the efficiency impacts of herbicide-resistant weeds by comparing those farms with identified herbicide-resistant weeds and those without such pressure.

7.3 The Growth of Traits in Soybeans Beyond Herbicide Tolerance

The BES varieties examined in this study consisted primarily of those with herbicide-tolerant traits. While demand-side traits such as low-linoleic soybeans were available, they were not the focus of this study – which looked primarily at the production of soybeans. During the timeframe of this study, changes in the food use of soybean oil and overall vegetable oil market in the U.S. have changed dramatically. Trans fats have been phased out of numerous food products due to health and policy (regulatory) issues. Trans fats that are not naturally occurring in food can be produced with the partial-hydrogenation of oils to increase the stability of oils for high-heat purposes such as frying.

Soybean oil is a major source for oils that are partially-hydrogenated and thus lost more food use volume than other vegetable oils when trans fats were beginning to be phased out of diets. Soybean oil is still the largest volume vegetable oil in the U.S. for human consumption. Varieties such as high-oleic soybeans which present an alternative to provide higher-heat stability without any partial-hydrogenation thus present an opportunity for soybean growers to provide a vegetable oil with the functional traits desired without any trans fats. Acreage of high-oleic soybean varieties is expanding at the time of this writing – currently with the benefit of premiums paid through contractual production. As production of high-oleic soybeans increase, there is a potential for the production of BES soybeans with this trait to enhance crop efficiency through increased prices.

The framework of this study can provide a basis for comparing the adoption and non-adoption of high-oleic soybeans – and other varieties – by segregating the results by the considered technology rather than the BES varieties for HT that were considered here. For consumption traits such as high-oleic soybeans, we would likely alter the cost-effectiveness and output mix efficiency analyses looking at the revenue generation from the enhanced soybeans.

7.4 Variable Returns to Scale Technologies

The study demonstrates there can be significant impacts on results when assuming constant returns-to-scale (CRS) and variable returns-to-scale (VRS) technologies in the modeling of efficiency.

The KS-test and T-test results indicated there was a difference in the productivity change measured in farms under CRS and VRS using the conventional Malmquist productivity index (MI) and the biennial Malmquist productivity index (BMI), respectively. While the decompositions of the MI and BMI into technical change (TC) and biennial technical change (BTC) were significantly different for a majority of the periods in the analysis when examining their empirical cumulative distribution functions with Kolmogorov-Smirnov goodness-of-fit hypothesis tests, the efficiency change (EC) and biennial efficiency change (BEC) generated empirical cumulative distribution functions (ecdfs) that were not statistically significantly different for a majority of the periods when tested.

The use of the biennial Malmquist productivity index was demonstrated here to provide measurements of productivity change and decompositions into efficiency change and technical change that can be used in examining efficiency for farms – or decision making units in general. Exploring the crop mix and impact of assumptions of available inputs and outputs that might constrain results would be of interest in applying the findings of this study for farm managers. Analyzing farms clustered by geography, climate, resource base, and crop mix and rotation might provide more appropriate benchmarks for comparing the farms in their efficiency and productivity analyses.

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