MANAGEMENT PRACTICES AND EFFICIENCY OF

FARMS IN THE WESTERN GREAT PLAINS

By

PILJA PARK VITALE

Bachelor of Science in Agricultural Economics
Seoul National University
Seoul, South Korea
1989

Master of Science in Agricultural Economics
Texas A & M University
College Station, Texas
2002

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Oklahoma State University
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Dissertation Approved:

Dr. Francis M. Epplin

Dissertation Adviser

Dr. B. Wade Brorsen

Dr. Arthur Stoecker

Dr. Kristopher Giles

Outside Committee Member

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Abstract: This dissertation is composed of four papers that have been produced as part of a research project designed to increase winter wheat productivity by suppressing cereal aphids in the Western Great Plains of the U.S. One hundred forty one farms were surveyed across six states in 2002-2005. The first paper was targeted to find the effect of crop diversity for traditional wheat dominant farms. The second paper was designed to determine if management practices such as tillage, crop diversity, wheat variety selection, and insecticide use affect wheat grain yield and net returns. Econometric methods were used to estimate wheat grain yield and net returns response to management practices. The third paper was designed to determine the relative performance of the farms as measured by technical and economic efficiency using a data envelopment analysis input oriented approach. The fourth paper was designed to compare two different methods, data envelopment analysis and stochastic frontier analysis, for measuring farm efficiency using an output oriented approach. Tobit models were used to estimate the relationships between farm efficiency and farm characteristics and management practices.

A major finding is that farms that exhibited the greatest level of flexibility in terms of crops grown, tillage systems used, and insecticide use, produced the greatest net returns per acre. Farms that have equipment enabling production with either tillage or with no-till, and farms that have the openness to use insecticide when warranted, and farms that have the flexibility to grow a variety of crops in response to agronomic and market conditions, will have the opportunity to earn more income than farms tied to the production of only wheat. Technical efficiency as measured by data envelopment analysis was found to be positively related to farm size, proportion of crop land that was cash rented, and operator education. Both efficiency estimation approaches found that the average farm in the sample operated under decreasing returns to scale and that farm size significantly affected technical efficiencies. The two approaches produced different estimates for technical efficiency scores, but gave similar results for returns to scale, and for determining factors affecting efficiency.

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PREFACE

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CHAPTER I

CROP DIVERSITY ON TRADITIONAL WHEAT FARMS OF THE GREAT PLAINS

Abstract

Historically, the vast majority of cropland in the western Great Plains was either seeded to continuous monoculture wheat or was in a wheat-fallow rotation. The objective of this chapter is to determine the combined effects of crop diversity and tillage on wheat grain yield and net returns for farms in the traditional wheat region of the western Great Plains. Farm level data were obtained for four crop production seasons. Crop diversity was relatively more important to system economics than type of tillage used. Net returns per acre were greater on farms that included a diversified cropping system.

Introduction

Prior to implementation of the 1996 Farm Bill (Freedom to Farm Bill), the vast majority of cropland in the western Great Plains of the U.S. was either seeded to continuous monoculture wheat or was in a wheat-fallow rotation. The most economical means for producing wheat in the region, given the available technology, included some tillage operations. Tillage was used to manage weeds and diseases, and to prepare a seedbed.

The 1996 change in federal policy, that eliminated the requirement of seeding wheat base acres to wheat to maintain eligibility for program payments, enabled farmers to plant crops other than wheat on wheat base acres and enabled them to rotate crops without jeopardizing federal crop subsidies. Changes in tillage, seeding, and weed control technology have enabled more intensive cropping in the region. Improvements in drills and air seeders facilitate successful plant establishment in fields with substantial surface residue.

Tillage systems that reduce the risk of soil erosion from more intensive cropping as well as the development of chemical herbicide systems that provide alternatives to tillage for managing weeds, have made it technically feasible for producers in the region to reduce the number of tillage operations, and to diversify beyond continuous wheat.

Agronomists have long advocated that farmers use crop rotations to diversify their cropping operations to help manage weeds, diseases, insects, and soil fertility. Designed experiments to compare the side-by-side performance of one or more multi-year crop rotations with one or more monocropping systems are substantially more expensive and more difficult to execute than monocrop studies. In addition, depending on the number of crops in the rotation, they may require a number of years. Only a limited number of crop rotation studies have been conducted in the traditional wheat production region of the western Great Plains.

Zentner et al. (2002) found that a four year spring wheat-flax-winter wheat-pea rotation generated greater net returns than a wheat-fallow system in the Canadian Prairies. Lyon et al. (2004) reported that rotations including wheat and forage crops produced greater net returns per acre than traditional wheat-fallow systems in Nebraska. Bushong et al. (2012) found that expected net returns of a two-year winter canola-winter wheat rotation exceeded the net returns of a continuous winter wheat system in Oklahoma.

Soil scientists recommend that farmers maintain surface residue to mitigate soil erosion. However, experiment station studies conducted in Oklahoma have found that when wheat is grown year after year in the same field, grain yield is often reduced when a substantial quantity of wheat residue from the previous wheat crop is retained on the surface (Daniel et al. 1956; Zingg and Whitfield 1957; Harper 1960; Davidson and Santelmann 1973; Heer and Krenzer 1989; Epplin et al. 1994; Epplin and Al-Sakkaf 1995; Decker et al. 2009). In continuous wheat production systems, more disease inoculum is present on wheat residue left above the soil surface with no-till than with conventional tillage. With a disease such as take-all root rot, increased residue results in increased amounts of inoculum because the fungus that causes take-all survives on the residue (Edwards et al. 2006; Decker et al. 2009). Foliar diseases such as tan spot and stagonospora glume blotch are also more common in continuous wheat fields that have surface residue from the previous year's crop (Edwards et al. 2006). As a consequence, under Oklahoma conditions, the expected grain yield from no-till continuous wheat is lower than the expected grain yield from continuous wheat produced on soils with less surface residue at planting.

The economic consequences of diversified cropping systems across tillage systems for farms in the western Great Plains have not been fully explored. The objective of the research reported in this paper is to determine the combined effects of crop diversity and tillage system on wheat grain yield and net returns for farms in the traditional wheat region of the western Great Plains.

Data and Methods

Cooperative extension service county educators, managers of farmer owned cooperatives, and executives from producer organizations helped to identify farmers for participation in the study based on volunteering. These participants were a non-random sample of wheat producers in the Western Plains. Data were obtained from a series of face-to-face interviews conducted with 141 farmers over four complete cropping seasons from 2002 through 2005. Counties in which the farms are headquartered and the number of farms surveyed per county are shown in Figure I-1. Each of the farm managers attended a group annual meeting. A comprehensive on farm interview was conducted annually on each farm to obtain detailed information about the farming operations for the year.

The data provided in the farm surveys were used to prepare detailed cost and return enterprise budgets for each crop for each farm for each year (AAEA Task Force, 2000). Total revenue produced by all crops, including hay and forage, included direct revenue (yield times price), government payments (direct, counter cyclical, and loan deficiency), and crop insurance. Total costs included labor, fuel, repairs, seed, fertilizer, herbicide, hired custom operations, crop insurance premiums, overhead, operating interest (variable cost items), and depreciation, interest, and taxes, housing, and insurance (machinery fixed cost items). Overhead cost was included to account for shop utilities, supplies, tools, and pickup truck expenses. It was computed by multiplying variable cost before interest by 0.04. Operating interest was charged to account for the opportunity cost of annual operating capital. Land costs were excluded. Machinery and truck cost were computed based on agricultural machinery management engineering and cost parameters (ASAE 2002). Draft copies of each of these budgets were returned to the farmers who were asked to review and verify the information, check for errors, and provide corrections as warranted. Corrections provided by the farmers were incorporated and final budgets were produced for all crops. During the four years the weighted-average U.S. farm price received for hard red winter wheat was relatively stable ranging from $2.71 per bushel for the 2001-2002 crop year to $3.29 per bushel for the 2004-2005 crop year. Other grain prices were also relatively stable during this time period with the weighted-average U.S. farm price received for corn ranging from $2.00 to $2.42 per bushel (USDA, 2012).

Tillage was defined based on reported number of tillage operations. Tillage was separated into three discrete groups: no-till, minimum till, and conventional till. A farm was classified as no-till if the land was not tilled on the farm over the four years. A farm was classified as conventional till if the producer reported three or more tillage passes prior to seeding a crop. Farms that did not fit into the no-till or conventional till categories were designated as minimum till. Information regarding the level of surface residue at planting was not obtained. Depending on the type of tillage, it is possible that a farm classified as conventional tillage could have planted some crops into substantial surface residue. Also, based on the method of classification, a farm classified as conventional tillage, may have used no-till for some crops. For example, a farm that used three or more tillage passes prior to planting wheat, but then followed wheat with no-till soybeans was classified as a conventional tillage farm.

Many of the surveyed producers produced crops in addition to wheat which is the predominate crop grown in the dryland western plains. A continuous variable for diversity was defined based on the proportion of wheat plus fallow acres relative to total crop and fallow acres. A diversity ratio without fallow acres was also calculated based on the proportion of wheat acres relative to total crop acres excluding fallow acres. The regression results using diversity ratio without fallow acres are reported in the Appendix to chapter I. The farms were classified into three discrete groups. The groups are described as wheat-only, some diversity, and full diversity based on the ratio of the area of wheat and fallow acres relative to total crop and fallow acres. Farms that fell in the upper 25% of the diversification ratio were classified as wheat-only. Farms that fell in the lower 25% of the diversification ratio were classified as full diversity. Those farms in the middle 50% were classified as some diversity.

Regression analysis was used to determine the effect of tillage and crop diversity on wheat grain yield and net returns. Four annual observations were obtained from each of the 141 farms producing a panel (time series and cross section) data set. The SAS PROC MIXED procedure was used to estimate the models. Tillage, crop diversity, state, and years were included as fixed effects. The individual farms were treated as random effects. The base regression model was:

$$\textit{Wheat grain yield}_{it} \text{ or } \textit{Net return}_{it} = f\,(\textit{year}_t, \textit{state}, \textit{tillage}_i, \textit{crop diversity}_i, \textit{tillage}_i{*}\textit{crop diversity}_i, \textit{random producer}_i), \quad (1.1)$$

where t = years 2002, 2003, 2004, 2005; $i = 1,\ldots,141$ producers; *Wheat grain yield* is wheat grain produced per acre per year (bu); *Net Return* is average net returns across all crops per acre per year ($); *tillage* includes no till, minimum till, and conventional till as categorical variables; *crop diversity* includes wheat-only, some diversity, and full diversity as categorical variables, or, alternatively, the ratio of the sum of wheat and fallow to total cropped area as a continuous variable; *State* includes six states as categorical variables.

Results

Table I-1 includes a summary of the number of farms included in the sample categorized by state, by tillage system, and by their average wheat acres. Sixteen percent of the producers used no-till throughout each of four years for all crops grown on their farm. All crops seeded on the no-till farms were directly seeded into residue for each of the four growing seasons. In Colorado, 97% reported using no-till or minimum till. However, 76% of the Oklahoma producers reported using conventional tillage.

In all states but Texas, a greater proportion of land was cropped to wheat on conventional tillage farms than on no-till farms. On Oklahoma farms that used conventional tillage, 84% of the total land area cropped was seeded to wheat. However, only 49% of the land on the Oklahoma no-till farms was seeded to wheat.

Diversification was defined in terms of the proportion of crop acres seeded to wheat and fallowed relative to total crop acres (Table I-2). The least diversified 25% of the producers were classified as wheat-only. More than 94% of the crop acres on these farms were either seeded to wheat or fallowed. The middle 50% of the producers in terms of diversification were categorized in the some diversity group. On these "some diversity" farms, 73-81% of the crop acres were either seeded to wheat or in fallow. The most diversified 25% were classified as "full diversity". On these farms, 42-56% of the cropland was either seeded to wheat or in fallow. Cropping was most diversified in Kansas with 75% of the Kansas farms included in the full diversity group. Wyoming was least diversified with 43% of the Wyoming farms included in the wheat-only group.

Table I-3 includes results of the regression models for wheat grain yield as a function of tillage and crop diversity. Model 1 includes discrete variables for tillage and crop diversity. The model did not find any significant factors affecting wheat grain yields except for year and state. Model 2 includes the continuous variable for crop diversity. It did not find any significant factors affecting wheat grain yield. Model 3 includes a set of tillage by diversity interaction terms. Both no-till and minimum till by wheat-only interaction terms had negative (but insignificant) signs. The interaction between no-till and some diversity was significantly positive. Based on the log likelihood values, Model 3 has more explanatory power than either Model 1 or Model 2.

Table I-4 includes the findings from the regressions for net returns per acre across all crops grown on the farm as a function of tillage and crop diversity. All net return models show that tillage and crop diversity significantly affected net returns. This result is consistent with that reported by Decker et al. (2009) who found that net return from continuous grain-only wheat was greater from conventional till plots than from no-till plots in Oklahoma.

Based on Model 5, which used a continuous variable rather than discrete variables for crop diversity, net returns across all crops were increased by an average of $0.50 per acre per year for every one percent decline in the proportion of wheat and fallow acres to total cropped acres. Model 6 includes tillage by diversity interaction terms. Each of these terms is statistically significant and based on the log likelihood value, Model 6 has more explanatory power than either Model 4 or Model 5.

Table I-5 shows marginal effects of tillage and crop diversity on wheat grain yield (based on Model 3) and net return (based on Model 6). Tillage did not significantly affect wheat grain yield. However, yields were significantly greater on the full and some diversity farms than on the wheat-only farms. This finding is consistent with that reported by Williams et al. (2012) who found that the wheat grain yield in continuous wheat system was lower than that of wheat - sorghum rotation. Similarly, Bushong et al. (2012) found that wheat yields in a canola-wheat rotation were greater than wheat yields of continuous wheat.

Based on Model 6, the expected net return on farms in the full diversity category was greater than farms in the wheat-only and some diversity categories by $26/acre. This result is consistent with that reported by Zenter et al. (2002), Lyon et al.(2004), Willams et al. (2012) and Bushong et al. (2012).

Table I-6 includes a summary of the expected grain yield, based on model 3, and the expected net returns, based on model 6, across the three tillage and three crop diversity groupings. Most of the yields across the nine categories are not significantly different. The predicted yields for conventional tillage for both wheat-only and full diversity farms are greater, but not significantly so, than for no-till farms. However, the predicted wheat grain yield from the no-till some diversity group was significantly greater than that from the minimum till some diversity group.

Based on Model 6, predicted net returns of the conventional till full diversity group are greater than those of both the no-till full diversity and minimum till full diversity groups by $56 and $64, respectively. The predicted net returns of the full diversity conventional tillage group are significantly greater than those of the conventional tillage some diversity group. The models suggest that farms with more diversified cropping systems generate greater net returns per acre. Eight farms were included in the full diversity conventional tillage category. Four of these eight farms were located in Kansas, three in Oklahoma, and one in Texas. In addition to wheat, all eight produced grain sorghum, six produced alfalfa, three produced corn, and two grew cotton.

Conclusion

The objective was to determine the combined effects of crop diversity and tillage system on wheat grain yield and net returns for farms in the traditional wheat region of the western Great Plains. Data were obtained from each of four production seasons across a sample of 141 farms across six states. Based on the regression models estimated, predicted wheat grain yields were similar across each of three tillage categories and each of three levels of cropping diversity. A variety of tillage systems are observed on farms in the region. This suggests that wheat grain yield response does not differ greatly across tillage system.

The major finding of the study is that based on the estimated regression equations cropping diversity is associated with greater expected net returns per acre. The predicted net returns across all crops grown on the farms were greater for farms in the full diversity category across all three levels of tillage. Predicted net returns were $64/acre greater for farms in the full diversity conventional tillage group than for wheat-only conventional tillage farms. Similarly, predicted net returns were $5/acre ($10/acre) greater for farms in the full diversity minimum till (no-till) group than for wheat-only minimum till (no-till) farms. Diversified cropping systems may require more management skills and time. One limitation is that the cost data do not include a charge for management. In particular, crops such as alfalfa and cotton require more management than wheat. A second limitation is that cropping opportunities are constrained on some farms by the available soil resources and prevailing climate.

The findings suggest that farms in the region could benefit by identifying and implementing economically viable cropping alternatives that fit in a rotation with wheat. Additional experiments are warranted to identify potential crops for inclusion in crop rotations for the region and to compare the side-by-side performance of multi-year crop rotations with continuous wheat. Appropriately designed crop rotation studies are substantially more expensive and more difficult to execute than monocrop studies. However, the additional cost of these experiments should be weighed against the potential economic impact, which is considerable.

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Table I-1. Number of farms by state included in the sample and average wheat planted acres by tillage system by state, 2002-2005.

State	No Till			Minimum Till			Conventional Till		
	Farms (no.)	Wheat acres/yr (% of total cropped acres)	Farms by tillage system (%)	Farms (no.)	Wheat acres/yr (% of total cropped acres)	Farms by tillage system (%)	Farms (no.)	Wheat acres/yr (% of total cropped acres)	Farms by tillage system (%)
Colorado	8	2,811 (37[a])	23[b]	26	1,593 (43)	74	1	1,502 (40)	3
Kansas	2	734 (41)	17	4	944 (43)	33	6	953 (64)	50
Nebraska	3	541 (38)	21	8	729 (32)	57	3	827 (39)	22
Oklahoma	4	993 (49)	10	6	1,536 (66)	14	32	1,445 (84)	76
Texas	3	321 (55)	13	18	1,307 (57)	74	3	971 (43)	13
Wyoming	2	509 (33)	14	8	1,074 (47)	57	4	1,339 (46)	29
Total	22	-	16	70	-	50	49	-	34

[a] On average the eight Colorado no-till farms planted 2,811 acres of wheat per year. Wheat acres accounted for 37% of their total crop and fallow acres.

[b] Twenty three percent of the Colorado farms included in the sample used no-till exclusively over the four years for all crops grown on the farm.

Table I-2. Number of farms included in the sample by state and level of crop diversity.

	Number of Producers			Wheat and Fallow Acres (% of total cropped acres)		
State	Wheat-only	Some Diversity	Full Diversity	Wheat-only	Some Diversity	Full Diversity
Colorado	7	23	5	94	77	54
Kansas	2	1	9	96	81	42
Nebraska	1	7	6	97	79	46
Oklahoma	14	20	8	96	79	47
Texas	5	14	5	98	73	48
Wyoming	6	6	2	98	78	56
Total	35	71	35	-	-	-

Table I-3. Regression for wheat grain yield response to tillage, crop diversity, production year, and state (bu./acre/year).

Variables	Model 1		Model 2		Model 3	
Intercept[a]	25.08		26.73	***	26.64	***
Year						
2002	-10.37	***	-10.36	***	-10.35	***
2003	2.85	***	2.85	***	2.86	***
2004	-0.66		-0.66		-0.65	
State						
Colorado	0.14		0.47		-0.36	
Kansas	22.16	***	21.83	***	22.03	***
Nebraska	4.05		4.30		5.00	**
Oklahoma	14.10	***	14.1	***	14.90	***
Texas	-2.15		-1.99		-2.31	
Tillage						
No-till	1.08		0.97		-3.92	
Minimum till	-1.75		-1.76		-1.92	
Diversity (continuous)	-		-3.04			
Wheat-only (discrete)	-2.14		-		-3.29	
Some diversity (discrete)	0.049		-		-3.57	
Tillage*diversity						
No-till*wheat-only	-		-		-2.69	
No-till*some diversity	-		-		12.24	***
Minimum till*wheat-only	-		-		-0.74	
Minimum*some diversity	-		-		2.00	
-2 log likelihood value	4,144		4,146		4,129	

Note:* is significant at 10% level, ** is significant at 5% level, *** is significant at 1% level

[a] The intercept value accounts for the estimated wheat grain yield from wheat produced in Wyoming in 2005 with conventional tillage on a full diversity farm.

Table I-4. Regression for net returns across all crops response to tillage, crop diversity, production year, and state ($/acre/year).

Variables	Model 4		Model 5		Model 6	
Intercept[a]	61.07	***	83.82	***	93.32	***
Year						
2002	-12.95	***	-12.95	***	-12.95	***
2003	1.08		1.08		1.08	
2004	-6.43	*	-6.43	*	-6.43	*
State						
Colorado	5.22		2.93		2.21	
Kansas	40.21	***	39.52	***	33.54	***
Nebraska	-3.44		-4.98		-0.13	
Oklahoma	22.00	***	20.33	***	25.33	***
Texas	28.95	***	25.60	***	25.98	***
Tillage						
No-till	-19.59	***	-21.21	***	-56.08	***
Minimum till	-20.79	***	-21.53	***	-63.95	***
Diversity (continuous)	-		-50.06	***		
Wheat-only (discrete)	-23.83	***	-		-63.75	***
Some diversity (discrete)	-21.91	***	-		-62.17	***
Tillage*diversity						
No-till*wheat-only	-		-		53.90	**
No-till*some diversity	-		-		51.63	***
Minimum till*wheat-only	-		-		58.81	***
Minimum*some diversity	-		-		54.97	***
-2 log likelihood value	5,563		5,564		5,534	

Note:* is significant at 10% level, ** is significant at 5% level, *** is significant at 1% level

[a] The intercept value accounts for the net return from wheat produced in Wyoming in 2005 with conventional tillage on a full diversity farm.

Table I-5. Effect of tillage and crop diversity on wheat grain yield and net return, 2002-2005.

Wheat Grain Yield (bu/acre/year) estimate based on tillage and diversity			
Conventional till	29 (1.14)	Wheat-only	25 (2.13)b
Minimum till	27 (0.86)	Some diversity	30 (0.94)a
No-till	28 (2.22)	Full diversity	29 (1.09)a

Net return across all crops ($/acre/year) estimate based on tillage and diversity			
Conventional till	61 (3.91)a	Wheat-only	37 (7.33)b
Minimum till	35 (2.94)b	Some diversity	37 (3.22)b
No-till	40 (7.65)b	Full diversity	63 (3.73)a

Note: Letter lowercase ‘a’ is significantly greater than letter lowercase ‘b’ among the same column at the 5% level. Values in parentheses are standard deviations.
Estimated models were based on Model 3 for wheat grain yields and Model 6 for net returns.

Table I-6. Combined effect of tillage and crop diversity on wheat grain yield and net return, 2002-2005.

	Wheat-only	Some Diversity	Full Diversity
Number of producers			
Conventional till	18	23	8
Minimum till	16	39	15
No-till	1	9	12
Wheat Grain Yield (bu/acre/year) Estimate Based on Model 3			
Conventional till	28 (1.64)	28 (1.40)	31 (2.25)
Minimum till	25 (1.56)	28 (1.10)b	29 (1.55)
No-till	21 (6.00)	36 (2.12)a	27 (1.74)
Net Return Across All Crops ($/acre/year) Estimate Based on Model 6			
Conventional till	39 (5.64)	41 (4.83)B	103 (7.72)aA
Minimum till	34 (5.35)	32 (3.66)	39 (5.30)b
No-till	37 (20.62)	37 (7.30)	47 (5.95)b

Note: Letter lowercase ‘a’ is significantly greater than letter lowercase ‘b’ among the same column at 5% level; Letter uppercase ‘A’ is significantly greater than letter uppercase ‘B’ among the same rows. Values in parentheses are standard deviations.

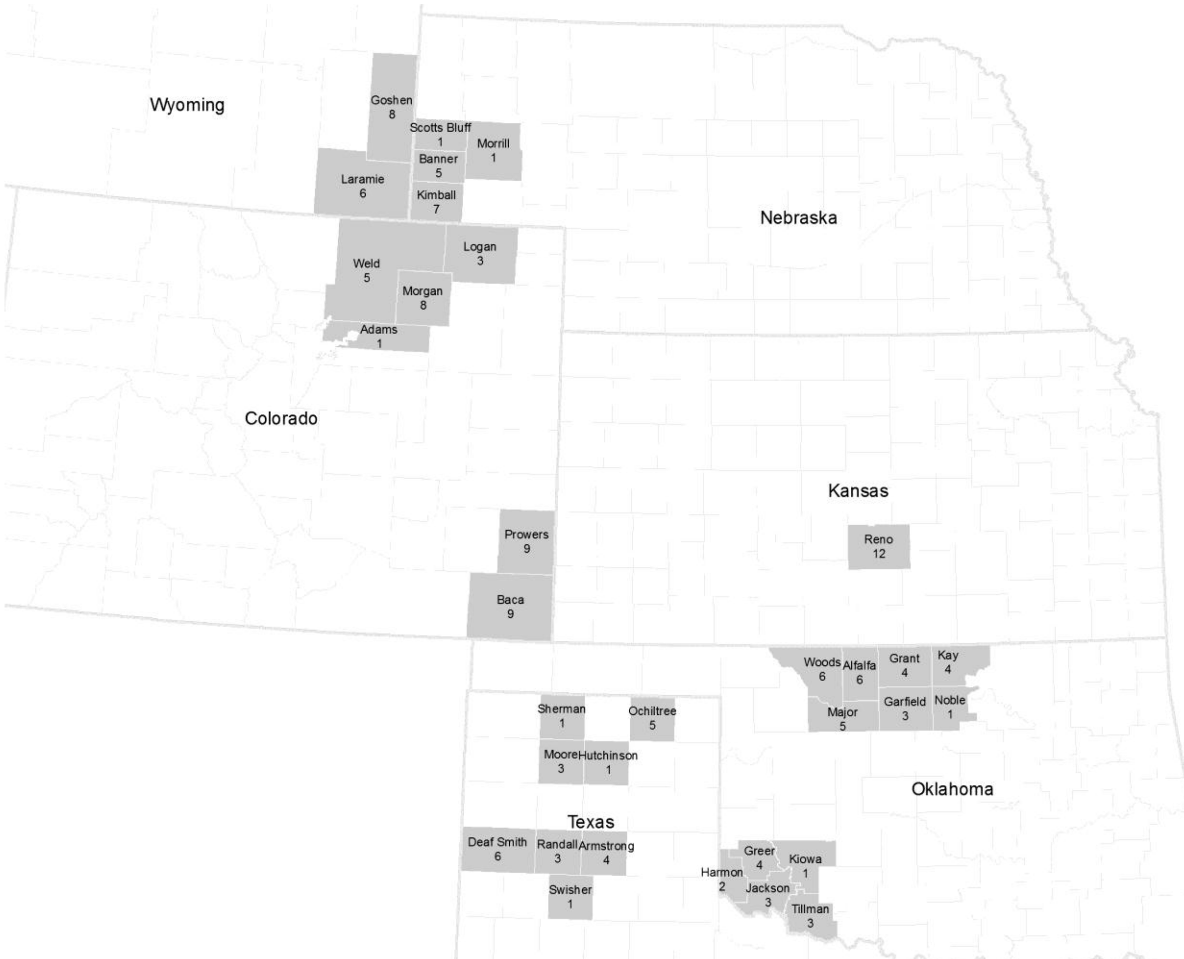

Figure I-1. Locations of farms included in the study.

Appendix for Chapter I

Table I-7. Regression for wheat grain yield response to tillage, crop diversity, production year, and state (bu./acre/year) with fallow not included in diversity variable.

Variables	Model 1		Model 2		Model 3	
Intercept[a]	25.51	***	27.75	***	29.88	***
Year						
2002	-10.36	***	-10.36	***	-10.36	***
2003	2.85	***	2.85	***	2.85	***
2004	-0.66		-0.66		-0.66	
State						
Colorado	-0.03		0.23		-0.16	
Kansas	22.00	***	21.71	***	22.06	***
Nebraska	3.93		3.89		4.76	**
Oklahoma	14.38	***	14.32	***	14.43	***
Texas	-2.02		-2.11		-1.68	
Tillage						
No-till	1.00		0.56		-4.85	
Minimum till	-1.80		-1.89		-6.51	*
Diversity[b] (continuous)	-		-4.49			
Wheat-only (discrete)	-2.97		-		-5.94	*
Some diversity (discrete)	-0.38		-		-6.65	**
Tillage*diversity						
No-till*wheat-only	-		-		-2.45	
No-till*some diversity	-		-		12.06	***
Minimum till*wheat-only	-		-		2.17	
Minimum*some diversity	-		-		6.93	*
-2 log likelihood value	4,142		4,144		4,129	

[a] The intercept value accounts for the estimated wheat grain yield from wheat produced in Wyoming in 2005 with conventional tillage on a full diversity farm.

[b] The criterion of diversity was defined as $\frac{\text{wheat acres}}{\text{total cropped acres}}$. Fallow net returns were allocated across crops according to the harvested crop acres in each year. Some fallow acres received revenue from government payments. Some fallow acres incurred costs for activities such as tillage, herbicide application and custom work.

Notes:* is significant at 10% level, ** is significant at 5% level, *** is significant at 1% level

Table I-8. Regression for net return across all crops response to tillage, crop diversity, production year, and state ($/acre/year) with fallow not included in diversity variable.

Variables	Model 4		Model 5		Model 6	
Intercept[a]	53.15	***	69.17	***	96.89	***
Year						
2002	-12.95	***	-12.95	***	-12.95	***
2003	1.08		1.08		1.08	
2004	-6.43	*	-6.43	*	-6.43	*
State						
Colorado	2.06		1.47		2.59	
Kansas	47.17	***	46.15	***	43.91	***
Nebraska	-3.28		-4.59		0.32	
Oklahoma	23.53	***	24.36	***	27.54	***
Texas	27.54	***	27.00	***	26.54	***
Tillage						
No-till	-16.02	***	-18.38	***	-62.27	***
Minimum Till	-19.75	***	-20.18	***	-60.85	***
Diversity[b] (continuous)	-		-37.09	***		
Wheat-only (discrete)	-16.95	***	-		-68.76	***
Some diversity (discrete)	-11.77	***	-		-60.85	***
Tillage*diversity						
No-till*wheat-only	-		-		46.57	**
No-till*some diversity	-		-		55.39	***
Minimum till*wheat-only	-		-		68.49	***
Minimum*some diversity	-		-		58.58	***
-2 log likelihood value	5,574		5,569		5,552	

[a] The intercept value accounts for the net return from wheat produced in Wyoming in 2005 with conventional tillage on a full diversity farm.

[b] The criterion of diversity was defined as $\frac{\text{wheat acres}}{\text{total cropped acres}}$. Fallow net returns were allocated across crops according to the harvested crop acres in each year. Some fallow acres received revenue from government payments. Some fallow acres incurred costs for activities such as tillage, herbicide application and custom work.

Notes:* is significant at 10% level, ** is significant at 5% level, *** is significant at 1% level

Table I-9. Combined effect of tillage and crop diversity on wheat grain yield and net return, 2002-2005 with fallow not included in diversity variable.

	Wheat-only	Some Diversity	Full Diversity
Number of producers			
Conventional Till	18	23	8
Minimum Till	16	39	15
No-till	1	9	12
Wheat Grain Yield (bu/acre/year) Estimate Based on Model 3			
Conventional Till	28 (1.65)	28 (1.29)	34 (3.04)
Minimum Till	24 (1.62)	28 (1.09)b	28 (1.44)
No-till	21 (4.24)b	35 (2.31)a	30 (1.66)
Net Return Across All Crops ($/acre/year) Estimate Based on Model 6			
Conventional Till	40 (6.05)B	48 (4.72)B	109 (11.16)aA
Minimum Till	36 (5.94)	34 (3.98)	37 (5.28)b
No-till	25 (15.56)	41 (8.48)	47 (6.05)b

CHAPTER II

MANAGEMENT PRACTICES USED BY WHEAT PRODUCERS IN THE WESTERN GREAT PLAINS

Abstract

Producers in the Western Great Plains use a variety of production practices. The objective was to determine if selected management practices used by producers result in differences in wheat grain yield and differences in net return per acre across all crops grown on the farm. The specific practices evaluated included tillage systems, wheat variety selection, crop diversification, and insecticide use. Wheat grain yields were insensitive to most of production practices. However, the most diversified farms that on average seeded only 49% of their acres to wheat, generated an average of $39 per acre per year greater net returns compare to less diversified farms.

Introduction

Millions of acres in the Western Great Plains of the United States are seeded annually to wheat. In 2010 the crop produced $4.1 billion in revenue (NASS, USDA). Concentrations of a crop species are often associated with a buildup of persistent pests. Common wheat pests in the region include cereal aphids, specifically Russian wheat aphids (RWA) (*Diuraphis noxia*) and greenbugs (GB) (*Schizaphis graminum*). These aphids damage wheat by sucking phloem fluids and by injecting toxins into the plants. GB also transmit barley yellow dwarf virus which is a common significant vicious wheat disease (French and Elliott 1990; Webster et al. 1994; Brewer et al. 2001).

The aphids do not cause serious losses every year. However, sudden outbreaks occur when temperature, humidity, and wind speed are favorable, and when populations flourish, RWA can destroy a wheat crop in a relatively short time. GB outbreaks are common within a 5-10 year cycle. Routine estimates of historical damage are not available. However, Starks and Burton (1977) estimated that a GB outbreak in 1976 inflicted damages of $80 million in Oklahoma. Webster et al. (1994) reported that 20% of dryland winter wheat and 60% of irrigated wheat was infested by RWA in 1993. The dryland yield loss was estimated to be 3.3 million bushels with an economic loss estimated to be $12.6 million. Webster et al. (1994) also estimated that 41% of dryland and 93% of irrigated wheat was infested by GB in 1993 resulting in substantial economic losses.

Wheat breeders have developed some varieties that include resistance to some biotypes of GB and other varieties that include RWA resistance. Breeding resistance into varieties is challenging because byotypes with variable levels of virulence exist for both of these aphid species (Burd and Porter 2006; Weng et al. 2010; Randolph et al. 2009). Certain genes may provide resistance to one or more biotypes but not to all biotypes. Emerging biotypes are unknown until the populations of the more common biotypes are reduced by resistant varieties, and the subsequent increase in the populations of virulent biotypes. Although these aphids may infest fields planted to resistant wheat varieties, they inflict less damage on resistant varieties. Varieties that include resistance to some RWA biotypes include Yumar, Prowers 88, and Prairie Red. TAM 110 and TAM 112 may also include resistance to some GB biotypes .

Other wheat varieties include genes that provide resistance to some biotypes but are not designated as resistant. Wheat breeders are reluctant to designate a variety as resistant if it is not resistant to all known biotypes. They do not want producers to be misled into believing that if they plant the variety they will not have to scout for the presence of RWA and/or GB. USDA surveys, from 2000 to 2010, found that varieties listed as RWA resistant were seeded on less than

0.1% of the wheat acres across the region, with use in Colorado reported at 20%. Acreage seeded to varieties listed as GB resistant ranged from 1.1% to 5%.

Since, GB and RWA outbreaks are not expected to occur every year and may be managed with an application of a labeled insecticide for a cost of about $10 per acre, from a producer's perspective, the expected net returns are greater from a higher yielding variety (Doye and Sahs 2010). And, expected yield is the primary adoption criteria used by producers (Teetes 1994; Keenan and Burgener 2008; Texas A&M 2010). While some high yielding varieties may carry resistance to some GB and RWA biotypes they may not be designated as resistant. In Kansas and Texas variety trials, grain yields of varieties classified as resistant have on average been lower than yields of other varieties (KSU 2006-2010; Texas A&M 2006-2010). Yields of resistant designated varieties included in Colorado trials were similar to those of the best yielding varieties (CSU 2006-2010).

In some growing seasons, populations of GB and RWA are kept in check by natural occurring enemies such as lady beetles, nabid, green lacewing, and parasitic wasps. In the 1990s entomologist released an introduced parasitoid, *Aphidius colemani*, which is indigenous to India, in many locations in the western United States in an effort to control RWA (Jones et al. 2003). Use of natural enemies is an integrated pest management (IPM) tool to maintain populations of GB and RWA below economic injury levels. However, when the populations of GB and RWA exceed economic injury levels, economics dictates the use of a labeled broad spectrum insecticide that is effective for reducing pest numbers but will also reduce the populations of the natural enemies.

Diversification of crops and crop rotations are also considered to be IPM practices. For example, Andow (1991) found that parasitoid populations are more abundant and effective in fields in which crops are rotated. Similarly, Gardiner et al. (2009) found that crop diversity and diversity of plants in the region of soybean fields influenced both the level of pest suppression and damage inflicted by soybean aphids.

Tillage is used to control weeds and to prepare seedbeds and pest populations are influenced by tillage. For example, Burton and Krenzer (1985) found that GB populations are often greater in conventionally tilled fields with little surface residue than in adjacent no-till fields with substantial surface residue. Hesler and Berg (2003) also found that conventional tillage was associated with greater infestations of cereal aphids, and a greater incidence of barley yellow dwarf virus than plots on which substantial surface residue was maintained. However, Royer et al. (2009) postulated that increases in Hessian fly infestations in Oklahoma are correlated with an increase in the use of no-till for growing wheat.

In continuous wheat production systems more disease inoculum is present on wheat residue left above the soil surface with no-till than with conventional tillage. With a disease such as take-all root rot, increased residue results in increased amounts of inoculum because the fungus that causes take-all survives on the residue (Edwards et al. 2006; Decker et al. 2009). Foliar diseases such as tan spot and stagonospora glume blotch are also more common in no-till plots and also reduce grain yield potential (Edwards et al. 2006). For some pests, no-till may be classified as an IPM technique. However, for other pests and diseases conventional tillage serves as an IPM tool.

The evaluation of IPM practices is complicated in part because of IPMs public goods characteristics and in part because of the potential external consequences. Fernandez-Cornejo and Ferraioli (1999) found that biological methods tended to reduce pesticide use and toxicity, while scouting resulted in an increase in pesticide use and toxicity on peach orchards. Hubbell (1997) found that the number of insecticide applications in apple orchards was highly correlated to insecticide efficacy, rate per application, month of treatment, and method of application. Fernandez-Cornejo et al. (1994) found that vegetable producers classified as IPM adopters managed larger farms, had more irrigated acres and used more family labor than nonadopters. Hubbell et al. (2001) found that lawn care and landscape maintenance firms respond to economic incentives and use IPM practices when it is economical to do so. Dumas and Goodhue (1999) produced an estimate of the economic consequences of the cotton boll weevil eradication program in North Carolina, South Carolina and Georgia. They found that during the eradication phase (1965-1985), cotton acreage decreased, but during the maintenance phase (1985-1995), cotton acres increased in part due to the reduction in boll weevils.

Estimates of the aggregate value and economic consequences of IPM practices for wheat, such as the development and release of GB and RWA resistant wheat varieties and of the release of introduced enemies such as parasitic wasps, have not been produced. Some wheat producers in the Western Great Plains plant RWA and/or GB resistant wheat varieties and others do not. Some use diversified cropping systems and others continuously crop their fields to wheat. Some use no-till practices and others use tillage. Insecticide use among wheat farmers in the region varies considerably. Most commonly, producers either combine a prophylactic insecticide application during planting or fertilization, or do not use insecticides. A small percentage of producers scout for aphids before making an economically justifiable insecticide application. While the economics of each of these production practices can be tested in standard experiment station replicated trials, the consequences of combinations of these practices on net returns at the farm level have not been determined. Since we observe a myriad of practices, it is reasonable to hypothesize that the economic consequences are ambiguous. The objective of the research reported in this paper is to determine if selected management practices used by wheat producers in the Western Great Plains result in differences in wheat grain yield and net returns. The specific practices to be evaluated include tillage systems, variety selection, crop diversification, and insecticide use.

Data

Data were obtained from a series of face-to-face interviews conducted with 141 producers over four years. Cooperative extension service county educators, managers of farmer owned cooperatives, and executives from producer organizations helped to identify wheat producers for participation in the study. These participants were a non-random sample of wheat producers in the Western Great Plains. One hundred forty five were identified and 141 producers provided data for four complete cropping years from 2002 through 2005. Participants were included from six states: 35 from Colorado, 12 from Kansas, 14 from Nebraska, 42 from Oklahoma, 24 from Texas, and 14 from Wyoming. Each of the producers attended an annual meeting. In addition, a comprehensive on farm interview was conducted annually on each farm to obtain detailed information about the farming operations for the year. To compensate participants for their time and travel cost, each participant was paid $250 for the group annual meeting and $100 for the annual on farm interview.

Tillage was defined based on reported number of tillage operations conducted in the field. Tillage was separated into three discrete groups: no-till, minimum till, and conventional till. A farm was classified as no-till if the land was not tilled on the farm over the four years. A farm was classified as conventional till if the producer reported three or more tillage passes prior to seeding a crop. Farms that did not fit into the no-till or conventional till categories were designated as minimum till.

Many of the surveyed producers produced crops in addition to wheat. Reported crops included sorghum, corn, soybean, millet, other grains, sunflower, oats, cotton, alfalfa, other hay, and forage. The producers were classified into three groups according to their level of cropping diversity which was defined based on the proportion of wheat acres relative to total cropped acres over the four years. The groups are described as wheat-only, some diversity, and full diversity. The criterion of classification is the following:

$$\text{diversity ratio} = \frac{\text{wheat planted acres} + \text{fallow acres}}{\text{total crop} + \text{fallow acres}} \text{ over four years.}$$

Farms that fell in the upper 25% of the diversity ratio were classified as wheat-only. Farms that fell in the lower 25% of the diversity ratio were classified as full diversity. Those farms in the middle 50% were classified as some diversity. A diversity ratio without fallow acres was also calculated based on the proportion of wheat acres relative to total crop acres excluding fallow acres. The regression results using diversity ratio without fallow acres are reported in the Appendix to chapter II.

A farm on which one or more acres during the four years, were planted to a variety with specified resistance to either RWA or GB, was classified as a farm that planted resistant varieties. Similarly, a farm on which insecticide was used on one or more acres during the four years was classified as an insecticide using farm. Some farms included in the plant resistant variety category did not plant resistant varieties every year; the number of observations in the category varies across years. This is also the case for the insecticide use category. Interaction terms such as year by insecticide use, tillage by diversity, and diversity by planting resistant varieties, were also considered. These management practice classifications are summarized in table II-1.

Computation of net returns

The data provided by the producers were used to prepare detailed cost and return enterprise budgets for each crop for each farm for each year (AAEA Task Force 2000). Net return per acre was determined for all crops because management practices affected not only wheat but other crops grown on the farm. Total revenue and total cost were computed based on survey results. Total revenue included the sum of gross returns from all crops (yield times price), government payments (direct payments, counter cyclical payments, and loan deficiency payments), and crop insurance.

Total costs included labor, fuel, repairs, seed, fertilizer, herbicide, hired custom operations, crop insurance premiums, overhead, and operating interest (variable cost items) and depreciation, interest, taxes, housing, and insurance (fixed cost items). Overhead cost was included to account for shop utilities, supplies, tools, and pickup truck expenses. It was computed by multiplying variable cost before interest by 0.04. Operating interest was charged to account for the opportunity cost of annual operating capital. Land costs were excluded. Labor cost included the cost of hired labor as well as the opportunity cost of family labor used to conduct machinery field operations. Machinery and truck cost for hauling were computed based on agricultural machinery management engineering and cost parameters (AAEA Task Force 2000; ASAE Standards 2002).

The sample of farms included in the study was not randomly drawn. To determine if the findings were representative of farms in the region that predominately produce wheat, estimates obtained were compared to those reported by the USDA. The USDA conducts random surveys to produce estimates of wheat production costs and returns. The estimates of wheat cost and returns for the USDA Prairie Gateway Region for the years 2002-2005 are reported in Table II-2. The Prairie Gateway Region includes parts of Colorado, Kansas, Nebraska, New Mexico, Oklahoma, and Texas. Average values for selected items obtained from these three states are also reported in Table II-2. A t-test was conducted to determine if the mean values were different between the two samples. The hypotheses of no difference were not rejected for cost of custom operation, fertilizer, revenue from wheat grain, and total gross revenue. However, farm size was statistically significantly different between the two samples. The sample of farms included in this study planted significantly more acres per year to wheat (1,380) than the farms in USDA sample (395 acres per year). Based on these findings, the production practices on the sample farms are assumed to be representative of wheat farms in the region. However, the sample farms are substantially larger.

Models

Wheat yield response is modeled as a function of year, state, tillage (no-till, minimum till and conventional till), insecticide use (use vs. not use), use of RWA and GB resistant wheat varieties (use vs. not use), crop diversity (wheat-only, some diversity, full diversity), and interaction between year and insecticide use. The yield response model contains both fixed and random effects. All of the explanatory variables were designated as fixed effects. The farm specific effect, u_i, was included as a random effect. The response model for winter wheat yield is expressed as:

$$Q_{it} = \alpha + \sum_{l=1}^{3}\beta_l Y_{lt} + \sum_{k=1}^{5}\delta_k Z_{ks} + \sum_{m=1}^{2}\eta_m T_{mi} + \gamma_1 I_{it} + \gamma_2 Vr_{it} + \gamma_3 Vg_{it}$$
$$\sum_{j=1}^{2}\gamma_j D_{ji} + \sum_{n=1}^{3}\lambda_n Y_{ni} I_{nit} + u_i + \varepsilon_{it}, \qquad (2.1)$$

where index i denotes 1,..,141 farms; t refers to the four years included in the sample; the s set includes the six states; m includes the set of three tillage categories; j includes the set of three levels of crop diversity; Q_{it} is winter wheat yield from farm i in year t; Y_{lt} is a dummy variable for year t; Z_{ks} is a dummy variable for state s; T_{mi} is a dummy variable for tillage m; I_{it} is a dummy variable for insecticide use; Vr_{it} is a dummy variable for use of RWA resistant wheat varieties; Vg_{it} is a dummy variable for use of GB resistant wheat varieties; D_{ji} refers to the dummy variables for crop diversity; and $Y_{ni}I_{nit}$ is an interaction term between year and insecticide use. $\alpha, \beta_l, \delta_k, \eta_m, \gamma_1 - \gamma_3, \gamma_j, \lambda_n$ are parameters to be estimated; u_i is a farm random effect with distribution N $(0, \sigma_u^2)$; ε_{it} is a random error term with distribution N $(0, \sigma_t^2)$ and cov$(u_i, \varepsilon_{it}) = 0$.

A log likelihood function was used to estimate equation (2.1). Misspecification tests were conducted (McGuirk et al. 1986) and revealed that the random errors were not normally distributed and were autocorrelated among years. To correct this problem, state variables were replaced with dummy variables for county and random error terms was specified as first order autocorrelated. The generalized linear MIXED (GLIMMIX) procedure in SAS was used to estimate the model. Although the MIXED procedure could account for the panel data and could accommodate a flexible error structure, it strictly assumes a normal distribution of random errors. Alternatively, the GLIMMIX procedure was chosen. It conserves most of MIXED characteristics and corrects the standard deviations of the estimated coefficients using empirical (sandwich) estimation. The name stems from the layering of the estimator. An empirically based estimate of the inverse variance of the parameter estimates (the "meat") is wrapped by the model-based variance estimate (the "bread"). Empirical estimators are useful for obtaining inferences that are not sensitive to the choice of the covariance model according to the SAS manual(SAS Institute Inc 2010).

Statistical tests were conducted to determine if the predicted means differed across the extents of each practice. The Tukey-Kramer test was used to compare multiple means.

The model for net return is similar to equation (2.1) with net return ($/acre) rather than yields used as the dependent variable. Misspecification test revealed that the model for estimating net return was heteroskedastic. To correct for heteroskedasticity a square root transformation of the net return values (dependent variable) was conducted and the state dummy variables were replaced with the county average wheat yield as reported for the county in the particular year by the National Agricultural Statistics Service (USDA NASS). Two interaction terms, tillage by diversity and diversity by use of GB resistant wheat varieties, were added to enable passage of the misspecification tests. The regression results were fragile with respect to the choices of management practices. The following equation was estimated as the final model for net return.

$$(NR_{it})^{1/2} = \alpha + \sum_{l=1}^{3}\beta_l Y_{lt} + \delta\, ACY_{it} + \sum_{m=1}^{2}\eta_m T_{mi} + \gamma_1 I_{it} + \gamma_2 Vr_{it} + \gamma_3 Vg_{it}$$
$$\sum_{j=2}^{2}\gamma_j D_{ji} + \sum_{n=1}^{4}\lambda_n T_{ni} D_{ni} + \sum_{n=5}^{6}\lambda_n D_{ni} Vg_{nit} + u_i + \varepsilon_{it}, \tag{2.2}$$

where NR_{it} is net return across all crops grown on farm *i* in year *t* ($/acre/year); ACY_{it} is average wheat yield as reported by NASS for county in which farm *i* resides in year *t* (bushels/acre); $T_{ni}D_{ni}$ is a tillage by diversity interaction term; $D_{ni}Vg_{nit}$ is a diversity by use of GB resistant varieties interaction term. Other variables and indices are as previously defined.

Results

No-till was used for each of four years by 16% of the farms (Table II-3). All crops seeded on the no-till farms were directly seeded into residue for each of the four growing seasons. There was considerable variability across states. In Colorado, 97% reported using no-till or minimum till. However, 76% of Oklahoma producers reported using conventional tillage. The average Colorado farm cropped more total acres and planted more acres to wheat than producers in any of the other states. The average Colorado no-till farm included in the survey cropped 7,520 acres with 79% cropped to wheat or in fallow each year. Conventional tillage was used on only one Colorado farm. It was relatively smaller (3,800 acres), with 87% cropped to wheat or in fallow.

In Oklahoma and Kansas, farms that primarily produced wheat were associated with conventional tillage. For example, for the conventional tillage Oklahoma farms, 84% of the total land area cropped was seeded to wheat while only 68% of the land on the Oklahoma no-till farms was seeded to wheat. Experiment station studies conducted in Oklahoma have found that when wheat is grown year after year in the same field, grain yield is often reduced when a substantial quantity of wheat residue from the previous wheat crop is retained on the surface (Epplin and Al-Sakkaf 1995). This may explain why Oklahoma producers that produced primarily continuous wheat predominately use conventional tillage.

Table II-4 reports findings relative to crop diversity which was defined in terms of the proportion of crop acres seeded to wheat and fallowed relative to total crop acres. The least diversified 25% of the farms were classified as wheat-only. Across states, a range of 94-98% of the crop acres on these farms were either seeded to wheat or fallowed. The middle 50% of the farms in terms of diversity were categorized in the some diversity group. On these "some diversity" farms, across the six states, 73-81% of crop acres were either seeded to wheat or in fallow. The most diversified 25% were classified as "full diversity". On these farms 42-56% of cropland was either seeded to wheat or in fallow. Cropping is most diversified on the Kansas farms with 75% (9 farms) included in the full diversity group. Wyoming was least diversified with 46% (6 farms) included in the wheat-only group. Because of differences in weather and soils, producers in some counties within the region have more economically viable cropping alternatives.

Table II-5 includes a summary of the level of use of RWA and GB resistant wheat varieties. Across all states, 18% of the producers (15% of the observations since each user did not use them in each year) used RWA resistant varieties on one or more acres. More than half of Colorado producers planted RWA resistant wheat varieties. Among those producers that used RWA resistant varieties, the average area planted to the resistant varieties was 68% in Colorado and 26% (15% of the observations) in Nebraska. Across all states 21% of the producers planted GB resistant varieties on one or more acres. Over the four years 17-31% of Colorado producers and 33-50% of Texas producers planted GB resistant wheat varieties on one or more acres. The proportion of total wheat acres planted to GB resistant varieties on these farms was 79% in Texas, 68% in Colorado, and 26% in Wyoming. None of the Oklahoma and Kansas producers used varieties that were listed as GB resistant.

Over the four years across the 141 farms there were 564 opportunities for RWA and GB infestations. Insecticide was used for 12% of the total potential outbreaks (table II-6). However, not every acre was treated on these farms. None of the Nebraska and Kansas producers reported insecticide use to protect wheat during any of the four years. Producers who used insecticide treated more than 60% of their wheat planted acres. Insecticide use was more common on Texas farms. Lorsban and dimethoate were the most frequently reported insecticides used.

Management practices varied across farms and across states. Colorado producers had a greater propensity to use no-till and plant RWA resistant wheat varieties. However, they had less crop diversity and used insecticide. Kansas producers had more diversified cropping systems, were less likely to use insecticide for managing RWA and GB, and most Kansas producers did not plant resistant wheat varieties. Use of conventional tillage was most common in Oklahoma where none of the participants reported use of resistant wheat varieties, and they used significantly greater quantities of insecticide than producers in other states. Texas producers had a greater propensity to plant GB resistant varieties but used insecticide at the highest rate among states.

Regression results for wheat grain yield response to management practices are reported in table II-7. The parameter estimates for tillage system, crop diversity, RWA resistant varieties, and GB resistant varieties were not significant at the 5% level, indicating that wheat grain yield was not significantly affected by differences in these management practices. Use of insecticide significantly effected wheat grain yield at the 5% level. Significance of the interaction term between insecticide use and the dummy variable for the year 2003, suggests that the effect of insecticide use on grain yield differs from year-to-year. The estimated marginal effect, accounting for both the direct and interaction effects of insecticide use, shows that based on the regression model, on average over the four years, wheat grain yield was approximately 3.46 bushels per acre per year lower on fields that did not use insecticide.

Table II-8 includes the results of the regression model (equation 2-2) for net return across all crops grown on the farm. Tillage system, level of crop diversity, use of GB resistant varieties, and use of insecticide are all found to have significantly affected net returns. No-till and minimum till farms produced lower net returns than farms that used conventional tillage (table II-8).The marginal effect of tillage shows that on average, the farms in the conventional till category produced $13 per acre more than those in the minimum till category and those in the no-till category (figure II-1).

Table II-8 also shows that farms in the wheat-only and some diversity groups had significantly lower net return than farms in the full diversity group. Farms in the full diversity category produced $38/acre more than farms in the some diversity category and $40/acre more than those in the wheat-only category (figure II-1).

Net returns were not significantly different among observations in the planted RWA resistant wheat varieties category and those not in the category. However, observations in not planted GB resistant wheat varieties category were significantly lower than observations in planted GB resistant wheat varieties category. It indicates that observations in the planted GB resistant wheat varieties category produced on average higher net return of $19 per acre than observations in not planted GB resistant wheat varieties (figure II-1).

The farms on which insecticide was used made significantly more net return than the farms on which insecticide was not used (table II-8). The marginal effect of insecticide use indicates that farms which used insecticide produced significantly more net returns of $11 per acre per year compared to farms which did not use insecticide (figure II-1).

The crop diversity by tillage and the diversity by planting GB resistant varieties interaction terms are positive and significant (table II-8). F tests were used to find how these effects affect each other. Tests were performed by the LSMEAN SLICE command in SAS. No-till and conventional till affected each level of diversity differently but minimum till did not affect diversity; full diversity affected each level of tillage differently. This indicates that a farm that used no-till or conventional till should consider diversity. A farm in full diversity could consider tillage (Figure II-2). Figure II-2 also shows an interaction between diversity and planting GB resistant varieties. Planting and not planting GB resistant wheat varieties affected diversity differently; but only full diversity affected planting or not planting GB resistant wheat varieties differently. This indicates that a farm which practices full diversity could consider whether the farm plants or does not plant GB wheat resistant varieties.

Table II-9 includes the estimated net return based on the fitted regression model for each of the four categories: tillage system, level of diversity, insecticide use, and use of resistant wheat varieties. The findings reported in Table II-9 illustrate the economic consequences of the combined effects of each of the four production practices including the interactions. Farms on which insecticide was used on one or more crops for one or more years show an increase in net returns of $8 to $20 per acre depending on other practices. Based on the model, expected net returns were no different on wheat-only farms that used either GB or RWA resistant varieties on one or more acres in one or more years relative to the expected net returns on wheat-only farms that did not use resistant varieties. However, estimated net returns were greater on the some and full diversity farms that used resistant varieties.

For farms in the wheat-only and some diversity categories, estimated net returns do not differ much across tillage system. However, for farms in the full diversity category, expected net returns are greater for those farms in the conventional tillage category. Recall that if conventional tillage was used to produce one or more crops on the farm, it was classified as a conventional tillage farm. Some crops produced on farms classified as conventional tillage may have been produce with no-till methods.

The greatest estimated net returns per acre of $156 is for farms classified as full diversity, conventional tillage, planted resistant varieties, and used insecticide. Recall that if a farm used a GB or RWA resistant variety on one or more acres in one or more years, it was classified as a planting resistant variety farm. Similarly, if a farm used insecticide on one or more acres in one or more years it was classified as a farm that used insecticide. Further investigation revealed that eight of the 141 farms were in the full diversity, conventional tillage, and used insecticide category. In addition to wheat, all eight produced grain sorghum, six produced alfalfa, three produced corn, and two grew cotton. Six of the eight farms used no-till to produce some of their crops. They were classified as conventional tillage because they used conventional tillage for some crops. In addition to using diversified cropping systems, they diversified their tillage and they at least occasionally used insecticides. In other words they were flexible. Rather than using a rote plan to grow a single crop, they managed.

Conclusion and Implication

The objective of the research was to determine the combined effects of crop diversity, tillage system, use of insecticide, and use of either GB or RWA resistant wheat varieties on wheat grain yield and net returns for farms in the traditional wheat region of the western Great Plains. Data were obtained from each of four production seasons across a sample of 141 farms across six states.

Based on the fitted regression model, predicted wheat grain yields were not statistically significantly different across each of three tillage categories, each of three levels of cropping diversity, and did not differ across farms that used GB or RWA resistant wheat varieties relative to those farms that did not plant resistant varieties. However, wheat grain yields were significantly greater on farms that indicated use of insecticide on one or more acres in one or more years. Since a variety of tillage systems are observed on farms in the region, it is not surprising that wheat grain yield response was not found to differ significantly across tillage system. The association between the use of insecticide and significantly greater wheat yields is also not surprising. Prudent use of insecticide could be expected to protect against yield loss and insecticide is more likely to be used on crops with greater yield potential.

Based on the regression model, net returns were significantly affected by tillage system, level of crop diversity, use of resistant varieties, and use of insecticide. The major finding of the study is that based on the estimated regression equation for net returns across all crops grown on the farm, cropping diversity, tillage diversity, and prudent use of insecticide are associated with greater expected net returns per acre. The predicted net returns across all crops grown on the farms were found to be greater for farms in the full diversity category across all three levels of tillage. The full diversity farms, that were also in the conventional tillage category, produced greater expected net returns per acre than full diversity farms in either the minimum tillage or no-till categories. Farms were classified as conventional tillage if they used conventional tillage for one or more crops in one or more years. They may have used other tillage systems in some years for some crops. For example, six of the eight conventional tillage full diversity classified farms used no-till to produce some crops. All of these eight farms used insecticide on one or more crops in one or more years.

Farms that exhibited the greatest level of flexibility in terms of crops grown, tillage systems used, and insecticide use, produced the greatest net returns per acre. Theoretically, farm managers that have fewer constraints will have more opportunities to engage in profitable endeavors. Farms that have equipment enabling either production with conventional tillage or with no-till, and farms that have the openness to use insecticide when warranted, and farms that have the flexibility to grow a variety of crops in response to agronomic and market conditions, will have the opportunity to earn more income than farms tied to a single crop with a single production method.

To the extent that climate and soils permit, wheat-only farms in the region may benefit by identifying and implementing economically viable cropping alternatives in addition to wheat. When considering replacing existing machinery, farms that are constrained by available machines to a single tillage system may benefit by investing in a complement of machines that can be used in both no-till and conventional tillage environments.

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Table II-1. Management practice categories.

Management practices	Categories
Tillage	No-till, minimum till, conventional till
Diversity	Wheat-only, some diversity, full diversity
Planting resistant wheat varieties	Planting resistant wheat varieties, not planting
Insecticide use	Insecticide use, not use insecticide

Table II-2. Comparison of findings from USDA estimates of wheat cost and returns for the USDA Prairie Gateway region, 2002-2005, to average findings from the study survey for states included in both estimates.

		USDA COP Estimates[a]				Survey[b]			
Item	Units	2002	2003	2004	2005	2002	2003	2004	2005
Revenue from wheat grain	$/acre	65.49	100.23	101.32	98.27	54.64	104.73	88.48	94.96
Revenue from straw/grazing	$/acre	2.78	2.54	6.72	7.33	11.37	11.78	10.95	11.17
Total, gross revenue from production	$/acre	68.27	102.77	108.04	105.60	66.01	116.51	99.43	106.13
Seed cost	$/acre	4.53	5.25	5.42	5.70	7.75	7.79	7.81	7.78
Fertilizer cost	$/acre	14.18	18.54	19.84	23.24	18.41	21.55	25.20	24.59
Chemicals cost	$/acre	3.15	3.16	3.75	3.81	5.22	4.75	5.73	5.96
Custom operations	$/acre	6.61	8.05	6.24	6.29	5.74	7.51	7.20	7.85
Hired labor cost	$/acre	2.06	2.15	2.27	2.34	2.70	3.03	2.94	2.66
Wheat yield	bu/acre	22.2	35.2	29.2	31.7	20.3	34.0	31.2	32.7
Wheat acres	acres	347	347	443	443	1,314	1,447	1,298	1,463

[a] Estimates produced by the USDA cost of production surveys. The Prairie Gateway Region includes parts of Colorado, Kansas, Nebraska, New Mexico, Oklahoma, and Texas.

[b] Estimates produced by the current study.

Table II-3. Number of producers and total land cropped by tillage system, 2002- 2005.

State	No-Till		Minimum Till		Conventional Till		Total
	Number of Producers[a] (%)	Total Acres Cropped (% of wheat and fallow area)	Number of Producers (%)	Total Acres Cropped (% of wheat and fallow area)	Number of Producers (%)	Total Acres Cropped (% of wheat and fallow area)	Number of Producers (%)
Colorado	8 (23)	7,520 (79)	26 (74)	3,695 (87)	1 (3)	3,800 (87)	35 (100)
Kansas	2 (17)	1,784 (53)	4 (33)	2,175 (61)	6 (50)	1,493 (61)	12 (100)
Nebraska	3 (21)	1,432 (70)	8 (57)	2,263 (81)	3 (22)	2,108 (81)	14 (100)
Oklahoma	4 (10)	2,035 (68)	6 (14)	2,327 (84)	32 (76)	1,716 (84)	42 (100)
Texas	3 (13)	585 (76)	18 (74)	2,279 (56)	3 (13)	2,226 (56)	24 (100)
Wyoming	2 (14)	1558 (85)	8 (57)	2,263 (94)	4 (29)	2,916 (94)	14 (100)
Total	22 (16)	-	70 (50)	-	49 (34)	-	141 (100)

[a] The % is the ratio of number of producers in each tillage grouping to total number of producers.

Note: Status was maintained throughout each of four years of observations. All crops seeded on the no-till farms were directly seeded into residue for each of the four growing seasons.

Table II-4. Number of producers by crop diversity

	Number of Producers			Wheat and Fallow acres (%) [a]		
State	Wheat-Only	Some Diversity	Full Diversity	Wheat-Only	Some Diversity	Full Diversity
Colorado	7	23	5	94	77	54
Kansas	2	1	9	96	81	42
Nebraska	1	7	6	97	79	46
Oklahoma	14	20	8	96	79	47
Texas	5	14	5	98	73	48
Wyoming	6	6	2	98	78	56
Total	35	71	35	-	-	-

[a] Wheat and fallow acres as a percentage of total acres cropped.

Table II-5. Number of observations by RWA and GB resistant wheat varieties planted

State	RWA			GB		
	Number of Observations[a]		Wheat Area Among Producers Who Planted (%)[b]	Number of Observations		Wheat Area Among Producers Who Planted (%)
	Planted	Not Planted		Planted	Not Planted	
Colorado	79	61	68	33	107	34
Kansas	0	48	-	0	48	-
Nebraska	2	54	26	4	52	16
Oklahoma	0	168	-	0	168	-
Texas	0	96	-	40	56	79
Wyoming	1	55	-	8	48	25
Total	82	482	-	85	479	-

[a] Four observations were obtained from each farm; one for each of the four years.

[b]The percentage of acres planted to resistant varieties relative to the total acres planted to wheat on those farms that used resistant varieties.

Table II-6. Number of producers that used insecticide and wheat acres treated with insecticide for managing RWA and GB. 2002-2005.

State	Number of Observations		Wheat Acres Treated Across All Wheat Acres (%)	Wheat Acres Treated on Farms That Used Insecticide (%)
	Used	Not used		
Colorado	18	122	11.6	54
Kansas	-	48	-	-
Nebraska	-	56	-	-
Oklahoma	28	140	16.5	65
Texas	18	78	18.6	84
Wyoming	6	50	2.4	39
Total	70	494	-	65

Table II-7. Effects of management practices on wheat yield.

Variables	Variables	Levels of Variables	Coefficient (bu./acre)	Standard Error
Dependent	Weighted average wheat yield (bu./acre/year)			
Independent	Intercept		47.9**[a]	4.11
	Year	2002	-9.27***	2.66
		2003	-5.16	2.86
		2004	0.18	2.01
	Location[b]	33 counties	***	
	Tillage	No-till	-0.36	1.60
		Minimum till	-1.19	1.19
	Crop diversity	Wheat-only	-1.67	1.49
		Some diversity	-0.10	1.34
	RWA resistant varieties	Not planted	-3.13	1.67
	GB resistant varieties	Not planted	-2.33	1.26
	Insecticide use	Not used	-5.27**	2.14
	Year x insecticide use	2002 x not used	-1.36	2.96
		2003 x not used	9.72***	3.18
		2004 x not used	-1.12	2.35
Number of observations	564			
Value of restricted log likelihood	-1,947			

[a] An * is significant at 10% level, ** is significant at 5% level, *** is significant at 1% level.

[b] County location variable was significant with F value 225. 59.

Notes: The intercept term reflects the value for conventional tillage, full diversity, planted RWA and greenbug resistant variety, and insecticide use.

Table II-8. Effects of management practices on net returns across all crops grown on the farm.

Variables	Variables	Levels of Variables	Coefficient ($/acre/year) [a]		Standard Error
Dependent	Weighted Average Net Return for All Crops (√$/acre/year)				
Independent	Intercept		8.95	***	1.25
	Year	2002	0.06		0.39
		2003	-0.06		0.27
		2004	-0.74	**	0.31
	County Wheat Yield [b]	Average	0.13	***	0.02
	Tillage	No-till	-2.77	***	0.70
		Minimum till	-3.32	***	0.69
	Crop Diversity	Wheat-only	-6.86	***	1.27
		Some diversity	-5.95	***	1.37
	RWA Resistant Varieties	Not planted	0.49		0.39
	GB Resistant Varieties	Not planted	-3.54	***	1.15
	Insecticide [a]	Not used	-0.83	**	0.38
	Tillage x Diversity	No-till x wheat-only	2.62	***	0.96
		No-till x some diversity	2.60	***	1.11
		Min-till x wheat only	4.06	**	0.93
		Min-till x some diversity	3.03	***	0.93
	Diversity x GB Resistance Varieties	Wheat-only x not planted	3.51	***	1.20
		Some diversity x not Planted	2.66	***	1.28
Restricted log likelihood	-1,388				

[a] An * is significant at 10% level, ** is significant at 5% level, *** is significant at 1% level.
[b] The average wheat yield (bu/ac) as reported by the National Agricultural Statistics Service for the year and county.
Notes: The dependent variable is the square root of the average net return ($/acre) weighted across all crops grown on the farm. The intercept term reflects the value for conventional tillage, full diversity, planted RWA and GB resistance varieties, and insecticide used. There were 564 observations.

Table II-9. Estimated net returns by tillage system, level of diversity and use or nonuse of resistant wheat varieties.

	Conventional Till	Minimum Till	No-Till
Used Insecticide			
	Planted Either GB or RWA Resistant Varieties		
Wheat-Only	32	41	30
Some Diversity	43	39	41
Full Diversity	156	84	95
	Did Not Plant GB or RWA Resistant Varieties		
Wheat-Only	31	40	30
Some Diversity	32	29	30
Full Diversity	80	32	38
Did Not Use Insecticide			
	Planted Either GB or RWA Resistant Varieties		
Wheat-Only	23	31	22
Some Diversity	33	29	31
Full Diversity	136	70	79
	Did Not Plant GB or RWA Resistant Varieties		
Wheat-Only	23	31	21
Some Diversity	24	21	22
Full Diversity	66	23	29

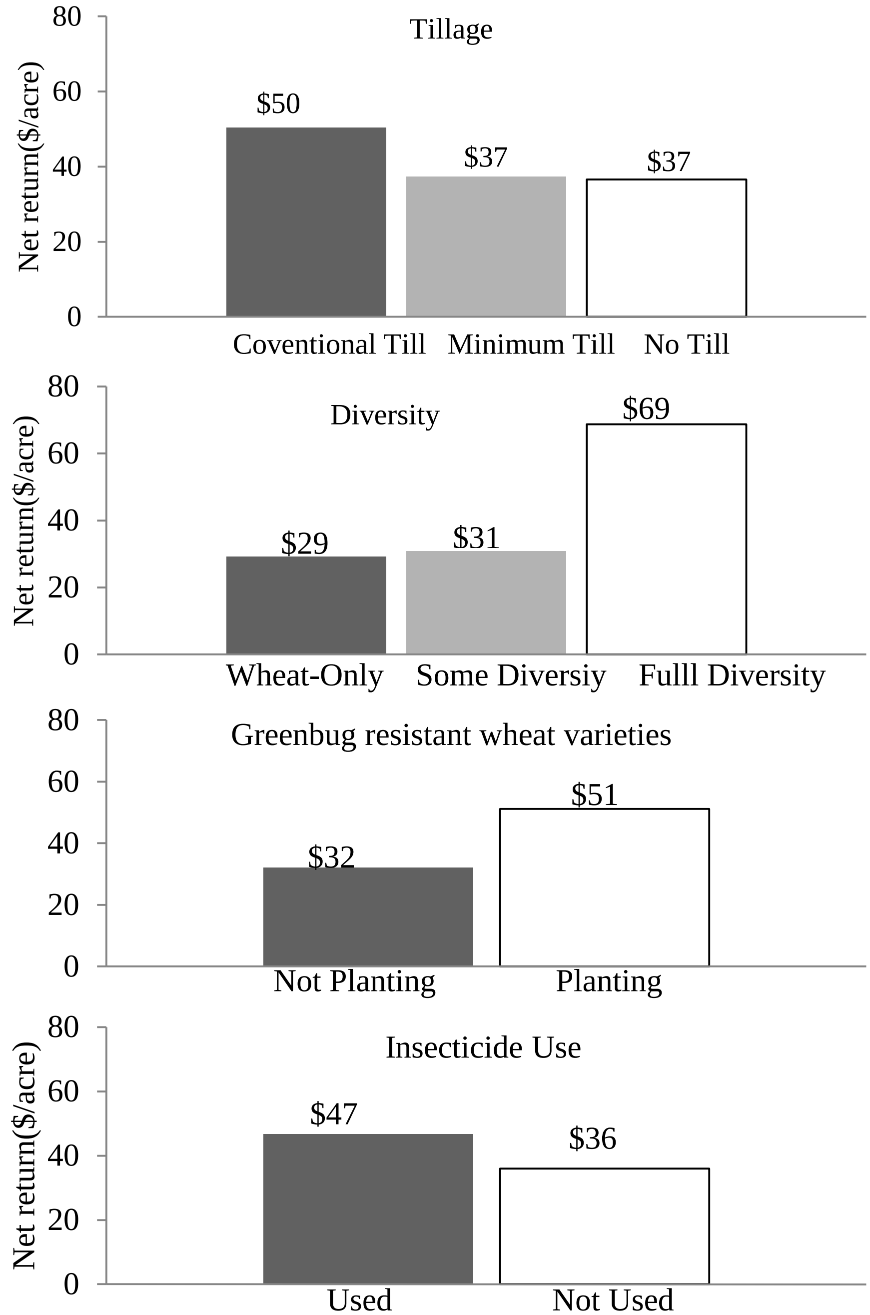

Figure II-1. Marginal effect of each management practice net returns across all crops grown on the farms.

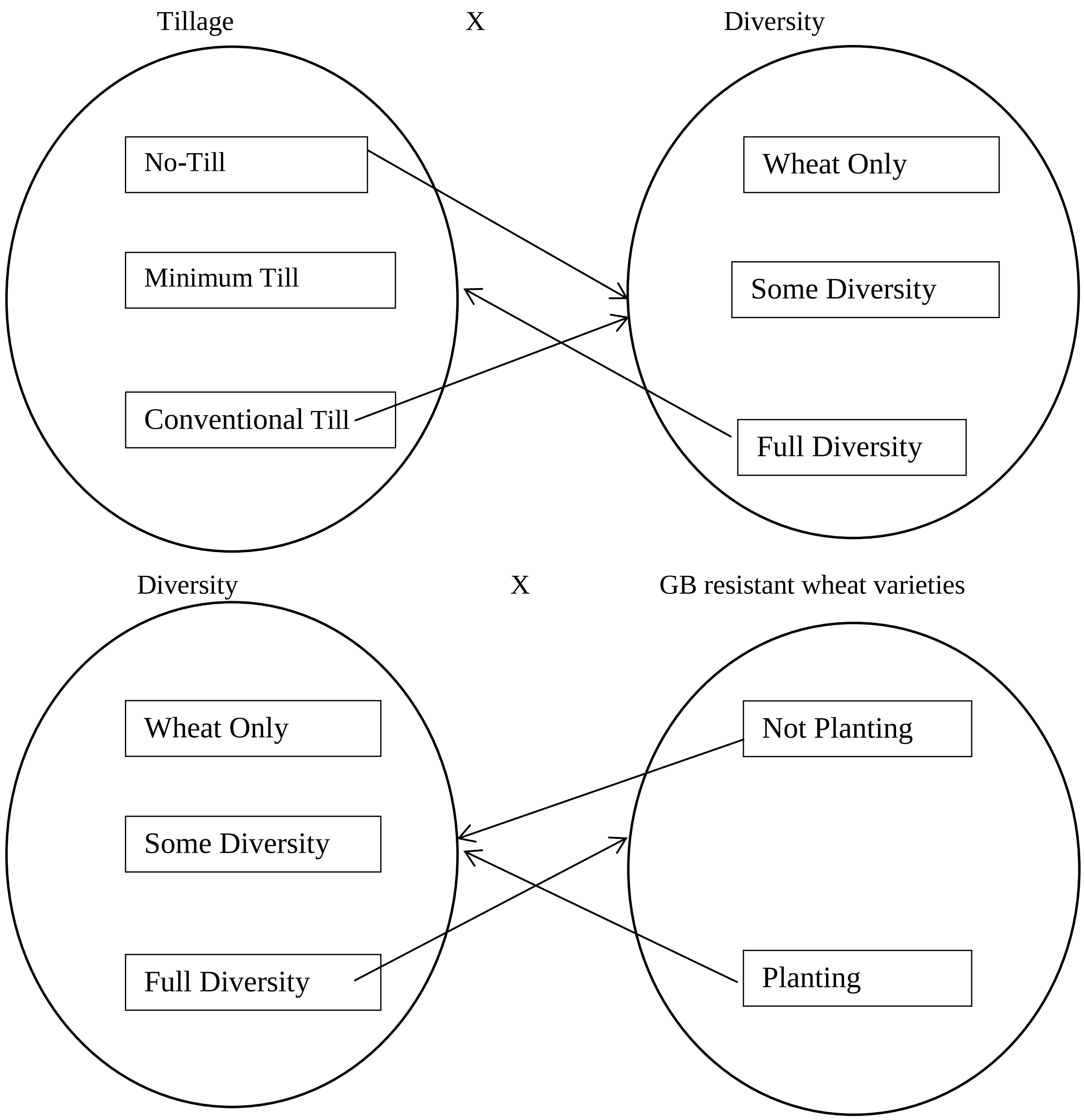

Figure II-2. Significant interactions between tillage and diversity, between diversity and use of GB resistant wheat varieties.

Appendix for Chapter II

Table II-10. Effects of management practices on wheat yield with fallow not included in diversity variable.

Variables	Variables	Levels of Variables	Coefficient (bu./acre)[a]	Standard Error
Dependent	Weighted Average Wheat Yield (bu./acre/year)			
Independent	Intercept		49.11**[a]	4.05
	Year	2002	-9.41***	2.67
		2003	-5.28	2.85
		2004	0.09	2.01
	Location[b]	33 Counties	***	
	Tillage	No-Till	-0.27	1.43
		Minimum Till	-0.93	1.06
	Crop Diversity[c]	Wheat-Only	-2.91**	1.37
		Some Diversity	-0.88	1.21
	RWA Resistant Varieties	Not Planted	-3.07*	1.67
	GB Resistant Varieties	Not Planted	-2.51**	1.26
	Insecticide Use	Not Used	-5.29***	2.13
	Year x Insecticide Use	2002 x Not Used	-1.18	2.97
		2003 x Not Used	9.63***	3.17
		2004 x Not Used	-1.26	2.35
Number of Observations	564			
Value of Restricted Log Likelihood	-1,931			

[a] An * is significant at 10% level, ** is significant at 5% level, *** is significant at 1% level.
[b] County location variable was significant with F value 226.

[c] The criterion of diversity was defined as $\frac{\text{wheat acres}}{\text{total cropped acres}}$. Fallow net returns were allocated across crops according to the harvested crop acres in each year. Some fallow acres received revenue from government payments. Some fallow acres incurred costs for activities such as tillage, herbicide application and custom work.

Notes: The intercept term reflects the value for conventional tillage, full diversity, planted RWA and greenbug resistant variety, and insecticide use.

Table II-11. Effects of management practices on net returns across all crops grown on the farm with fallow not included in diversity variable.

Variables	Variables	Levels of variables	Coefficient ($/acre/year) [a]		Standard error
Dependent	Weighted average net returns for all crops (√$/acre/year)				
Independent	Intercept		8.93	***	1.05
	Year	2002	0.10		0.39
		2003	-0.08		0.27
		2004	-0.75	***	0.31
	County wheat yield [b]	Average	0.13	***	0.02
	Tillage	No-till	-3.24	***	0.66
		Minimum till	-3.69	***	0.68
	Crop diversity	Wheat-only	-6.68	***	1.03
		Some diversity	-6.00	***	1.16
	RWA resistant varieties	Not planted	0.53		0.37
	GB resistant varieties	Not planted	-3.30	***	0.82
	Use of insecticide [a]	Not used	-1.00	***	0.39
	Tillage x diversity	No-till x wheat-only	3.43	***	0.93
		No-till x some diversity	2.63	***	1.16
		Min-till x wheat only	4.56	**	0.93
		Min-till x some diversity	3.14	***	0.91
	Diversity x GB resistance varieties	Wheat-only x not planted	3.00	***	0.91
		Some diversity x not Planted	2.74	***	1.03
Restricted log likelihood	-1,390				

[a] An * is significant at 10% level, ** is significant at 5% level, *** is significant at 1% level.

[b] The average wheat yield (bu/ac) as reported by the National Agricultural Statistics Service for the year and county.

[c] The criterion of diversity was defined as $\frac{\text{wheat acres}}{\text{total cropped acres}}$. Fallow net returns were allocated across crops according to the harvested crop acres in each year. Some fallow acres received revenue from government payments. Some fallow acres incurred costs for activities such as tillage, herbicide application and custom work.

Notes: The dependent variable is the square root of the average net return ($/acre) weighted across all crops grown on the farm. The intercept term reflects the value for conventional tillage, full diversity, planted RWA and GB resistance varieties, and insecticide used. There were 564 observations.

CHAPTER III

FACTORS AFFECTING EFFICIENCY OF WESTERN GREAT PLAINS FARMS

Abstract

Some farms are more profitable than other farms that grow similar crops under similar soil and climate conditions, indicating that some farm managers do a better job of selecting cropping systems and levels and types of inputs to use. The objective of this study is to determine the technical and economic efficiency of crop farms of the Western Great Plains and to find the sources of efficiencies. Data envelopment analysis was applied to data obtained from each of 141 farms over four years. Technical efficiency was positively related to farm size, proportion of crop land that was cash rented, and operator education.

Introduction

Acres plant to wheat in the U.S. have declined from 75 million in the fall of 1996, the year in which the 1996 Freedom to Farm bill was passed, to 56 million in the fall of 2013 (USDA 1950-2013). The decline in acres planted to wheat may have been in response to low economic returns relative to alternative uses of the resources used to produce wheat. Estimates of the value of wheat production less production costs are produced by the USDA. For the Prairie Gateway region, which includes parts of Colorado, Kansas, Nebraska, New Mexico, Oklahoma, and Texas, estimated average returns were negative for 13 of the 15 years between 1998 and 2012 (USDA ERS 1975-2012). Over this time period the average acre seeded to wheat in the region resulted in a loss of $50. However, as noted by Ali (2002) wheat production costs vary across farms and with farm size.

Weather and soil affect crop yields. However, the success of a producer also depends on his or her ability to determine the type and quantity of inputs to use and the mix of crops. Some farms generate positive net returns, whereas some farms generate negative net returns. Management decisions influence net returns. Measuring relative performance across farms and determining the characteristics of the more successful relative to the less successful farms has been of interest to researchers and extension educators (Dhuyvetter and Smith, 2010). In particular, factors affecting efficiency such as farm size and crop diversity have long been of interest to farm management specialists (Bynes et al. 1987; Weersink 1990; Kalaitzandonakes et al. 1992; Chavas and Aliber 1993; Featherston et al. 1997; Wu et al. 2003; Paul et al. 2004; Langemeier and Bradford 2005; Mugera and Langemeier 2011). The findings from these studies do not provide a consistent pattern regarding the consequences of farm size and cropping diversity on production efficiency. In this study, we measure the efficiency of farms in the Western Great Plains that primarily produce wheat and seek to determine the sources of efficiencies. The objective is to determine the technical and economic efficiency for crop farms of the Western Great Plains and to find the sources of efficiencies.

Potential Factors Affecting Efficiency

To find the source of efficiency, we hypothesize that efficiency is a function of farm size, crop diversity, number of cattle, tillage, proportion of cash rented land, number of machines, proportion of custom work, and farm demographic characteristics (age, education, family operating year, internet use). Based on previous research, the following variables are investigated.

Farm Operating Size: Most prior studies have found that within the sample of farms studied, large farms within the sample were relatively more efficient than smaller farms in the sample. Much of this efficiency gain can be attributed to the economies resulting when the fixed costs of farm machines and family labor are spread over relatively more acres. This in part explains why average U.S. farm size has increased and U.S. farm numbers have declined (Paul et al. 2004).

There are several measures of farm size. Mugera and Langemeier (2011) propose revenue produced by crops is a reasonable approach to differentiate farm size among crop farms. For the present study, farm size is classified based on average annual crop revenue. Farms with annual crop revenue in excess of $500,000 are classified as large; those with revenue between $250,000 and $500,000 are classified as medium; between $100,000 and $250,000 as small; and less than $100,000 as very small. We hypothesize that large farms are more efficient than small farms.

Crop Diversity: Wheat is the primary crop grown in the western Great Plains. Federal farm programs prior to the 1996 "freedom to farm" bill provided economic incentives for farmers in the region to grow wheat and to build and maintain wheat program base acres (Biermacher et al. 2006). The 1996 legislation removed the incentive to build and maintain wheat program base acres and enabled farmers to try other crops, including crop rotations on wheat base acres, without jeopardizing subsidies. This was a major departure from prior farm policy. However, information from designed experiments regarding potential economically viable cropping alternatives for the region was limited. Potential cropping alternatives include winter wheat-sorghum-fallow, winter wheat-corn-fallow, winter wheat–proso millet-fallow, and winter wheat-corn-proso millet-fallow (Elliot et al. 2006).

The crop diversity could increase efficiency by sharing inputs, and machine in different time by producing more crops (Chavas and Aliber 1993; Wu et al. 2003; Paul et al. 2004). However, this advantage could be reduced if the crops do not share the same inputs, or need more herbicides to remove summer weeds than growing wheat only (Olson and Vu 2007; Mugera and Langemeier 2011).

To measure crop diversity, we use the ratio of the area of wheat and fallow to total land cropped. Farms in the upper 25% of the diversity ratio were classified as wheat-only. Farms in the lower 25% of the diversity ratio were classified as full diversity. Those farms in the middle 50% were classified as some diversity. We expect that crop diversity could be positively correlated to the efficiency. Other definition of crop diversity could be considered without fallow acres because fallow is functioned as building up moisture rather than a crop.

Cattle: In the Great Plains, many crop farms also raise cattle. In the Southern Plains some winter wheat is grown as a dual purpose crop in which the wheat forage is grazed during the fall and winter and then cattle are removed to let the crop mature and produce a grain crop. Cattle production may enable farmers to more effectively use family labor in months that require few activities for the crop enterprises. However, the presence of livestock may compete with labor and hinder timeliness of crop production activities. Thus, we expect that as the number of cattle on a farm increases, the efficiency of crop production decreases.

Tillage: Minimum or no-till could reduce the cost of machinery fuel and repairs by reducing number of trips across the land relative to conventional tillage (Langemeier 2005). However, no-till requires more expensive drills and planters, and herbicide costs are often greater with no-till because herbicides are required to manage weed control. We hypothesize that reductions in tillage are positively related to efficiency. To measure tillage, we separate tillage into three discrete groups: no-till, minimum till, and conventional till. A farm was classified as no-till if the land was not tilled on the farm. A farm was classified as conventional till if the producer reported three or more tillage passes prior to seeding a crop. Farms that did not fit into the no-till or conventional till categories were designated as minimum till.

Proportion of cash rented land: Langemeier and Bradford (2005), who studied Kansas farms, and Olson and Vu (2007), who evaluated Minnesota farms, found that as the percentage of rented land relative to total land farmed increased, efficiency increased. However, Giannakas et al. (2001) found that the efficiency of farms in Saskatchewan, Canada, was inversely related to the percentage of rented land. We expect efficiency to be positively related to the proportion of land rented.

Machines: If a farm has more power and implement machines, a farm could use them to improve their efficiency. Machines could reduce average cost of producing crops by saving labor, whereas machines could not reduce average cost of producing crops by not operating optimal size. We separated machine into two categories: power and implement machine. Power machines include combines, tractors, self-propelled sprayers, trucks, and self-propelled swathers. Implement machines are those without an integral power unit and include sprayers, seeders, drills, plows, planters, fertilizer injectors, cultivators, chisels, and other tillage implements. We expect that the number of machines is positively related to efficiency.

Propotion of Cutom Work: Many farms hire custom operators to conduct some of the crop production activities. Common custom operations in the western Great Plains include spraying pesticide, spreading fertilizer, and crop harvesting. If the farm is able to obtain the custom work in a timely manner, it could increase efficiency. But, if the custom work is not performed in a timely manner, crop yield could be lost, resulting in a decrease in efficiency. We expect that the proportion of custom work to total number of field operations is negatively related to efficiency.

Farm Demographic Characteristics: Prior research has found that operator age, operator education, off farm income, and internet use affect efficiency. Age and off-farm income have been found to be negative related to efficiency (Langemeier and Bradford 2005, Olson and Vu 2007). Operator education is expected to be positively correlated with efficiency. Efficiency could be expected to be positively related to the number of years that the farm has been in the family. Farmers that have more knowledge of local conditions could help to improve efficiency. Internet use could assist with efficiency by providing timely information and access to production inputs.

Methodology

Estimating Efficiency

Methods for considering production efficiency were proposed by Koopmans (1951) and Farrell (1957). The nonpararmetric data envelopment analysis (DEA) approached developed by Charnes et al. (1978) is used in this paper. The DEA approach to measure efficiency does not require a functional form assumption and can consider multiple outputs as well as multiple inputs. DEA estimates efficiency by calculating the ratio of sum of weighted outputs to sum of weighted inputs. DEA determines the “best practice” efficient frontier. The efficiency of a specific firm or farm is determined by comparing the inputs used by the farm to those used on farms identified to be on the efficient frontier.

An input oriented model was used to estimate efficiency scores. The input oriented model estimates efficiency by minimizing input use subject to a given level of output. Model 1 of table III-1 calculates technical efficiency. Theta (θ) is a technical efficiency score and is bounded from zero to one. If theta is less than one, there exists technical inefficiency. Technical efficiency scores can be computed under variable returns to scale (TEVRS). Model 2 shows the equation of technical efficiency under variable returns to scale (TEVRS).

Scale efficiency (SE) can be calculated as:

$$SE = TECRS/TEVRS, \tag{3.1}$$

where TEVRS is score of technical efficiency under variable returns to scale and TECRS is the score of technical efficiency under constant returns to scale. If the scale efficiency score for a farm is equal to one, then the farm is said to be scale efficient. This means that the farm is found to be operating at a point along its cost curve consistent with constant returns to scale (CRS). If the scale efficiency score is different from one then the farm is said to be scale inefficient. Scale inefficiency may result from a farm operating in either an increasing returns to scale (IRS) region or decreasing returns to scale (DRS) region.

To determine if the farm is operating in the IRS or the DRS region, a second linear programming problem (non-increasing returns to scale (NIRS)) can be solved. Model 3 in Table III-1 includes the equations that may be solved to address the NIRS issue. If the NIRS score is the same as TECRS score, then the farm is found to be operating under IRS. Otherwise, the farm is found to be operation in the DRS region.

Model 4 is designed to minimize the cost of each farm to produce a given level of outputs. Then, economic efficiency (EE) can be calculated as:

$$EE = w_i x_i^* / w_i x_i. \tag{3.2}$$

where $w_i x_i^*$ is the solution of model 4, that is a minimum cost of *i*-th farm, and $w_i x_i$ is the actual cost of *i*-th farm. The economic efficiency (EE) score is the product of technical and allocative efficiency. If the economic efficiency score is one, the producers have the lowest unit cost of production. The allocative efficiency (AE) score measures whether a producer uses the correct combination of inputs given input and output prices. Allocative efficiency under variable returns to scale is calculated as:

$$AEVRS = EEVRS / TEVRS, \tag{3.3}$$

where EEVRS is economic efficiency under variable returns scale, TEVRS is technical efficiency under variable returns to scale.

This study uses the GAMS(GAMS Development Corporation 2009) computer software to formulate and solve the models 1, 2, 3, and 4. Median and Wilcoxon tests were used for testing mean difference of efficiency among the groups (i.e. state, size, and diversity) (Banker et al. 2010). The null hypothesis of the median and Wilcoxon test was that there was no mean difference of efficiency among the tested groups. If the null is rejected, the efficiency scores are reported to be significantly different among the groups.

Input Reduction to Achieving Koopmans Efficiency

The Koopmans (1951) definition of technical efficiency was used to determine input reduction for technically inefficient farms. Using linear programming, the efficient production frontier is piece-wise linear. If part of the frontier line is parallel with axes, it is called a slack. Figure III-1 illustrates slack. Farm B is located in parallel with farm C. Farm B and C are on the frontier by Farrell's definition (1957). However, farm B uses more input X2 compared to farm C by k amount. This k amount is slacks which are not used in production process. Thus, technical efficiency can be achieved with slacks. To overcome this limitation, Koopmans's (1951) definition for a technically efficient farm requires that the farm operate on the frontier and that all associated slacks are zero. Based on Koopmans's definition of technical efficiency, farm B may not be efficient, and inefficient farm E may reduce not only distance EI amount of inputs but amount of slacks IC to achieve technical efficiency. EI is called radial distance. The first step to find the radial and slack reduction to achieve the efficient frontier, is to solve model 1. The second step is to find input slacks by minimizing slacks given the efficiency scores from the first step based on Coelli et al.(2003). It is called a second-stage linear programing problem. The formulation is:

$$\begin{aligned} & Min_{\lambda, OS, IS} && -(OS + K1' IS) \\ & st && -y_i + Y\lambda - OS = 0 \\ & && \theta x_i - X\lambda - IS = 0 \\ & && \lambda \geq 0, OS \geq 0,\ IS \geq 0 \end{aligned}, \tag{3.4}$$

where OS is a vector of output slacks, IS is a K x 1 vector of input slacks, and K1 is a vector of ones, θ is the solution of first stage.

Estimation Factors Affecting Efficiency

To estimate factors affecting efficiency, efficiency scores obtained from the DEA method were used as dependent variables. The independent variables for factors affecting efficiency were described in the previous section. Banker (1993) shows that the estimators of DEA of the true inefficiency values are the density function of maximum likelihood . It is assumed a normal distribution for efficiency scores with mean u and variance constant σ^2. Chilingerian and Sherman (2012) state that although the distribution of DEA scores is never normally distributed and often skewed, the regression assuming a normal distribution can be informative. A Tobit model is assumed to be most appropriate because many efficiency scores were bounded by one. The available data included four annual observations on each farm. To estimate the model correctly given these panel data requires treating year and farm as either a fixed effect or as a random effect. Because unconditional Tobit fixed effects model is biased due to the fixed number of observations of cross section and time resulting in inconsistent estimates for fixed coefficients, a Tobit random effects model was chosen (Maddala 1987). The model can be specified:

$$Y_{it} = X_{it}\beta + u_i + e_{it} \quad \text{if } X_{it}\beta + u_i + e_{it} < 1 \tag{3.5}$$

$$= 1 \qquad \text{otherwise,}$$

where Y_{it} is a vector of efficiency scores (TEVRS, SE, AE, EE) at observation i year t, X_{it} is the matrix of independent variables for observation i year t, β is a vector of parameters, u_i is a vector of farm random effects distributed normally with mean 0 and variance σ_u^2, e_i is a vector of error terms distributed normally with mean 0 and variance σ_e^2. u_i and e_i are independent. The XTTOBIT command in STATA version 12 (Stata Corp LP 2012) was used to estimate the model.

Data

Data were collected from 141 farms located in Colorado, Kansas, Nebraska, Oklahoma, Texas, and Wyoming for each of four years, 2002-2005. For computing efficiency scores, total annual gross revenue received from all crops was used as output; machinery, seed, fertilizer, chemical, labor, land, and miscellaneous were used as inputs. The units for output and inputs were monetary dollars. Machinery included fuel, repairs, custom machine; chemicals included herbicide, insecticide, and fungicide. Labor included hired, operator and family labor for machine operations. Land was calculated as the product of the cash rent value of cropland in the county and the farm's harvested acres for all crops.

Land value information was not obtained in the survey conducted for the study. USDA cropland cash rent data were used to estimate an annual value for the cost of the land input. Cropland cash rent values for the 2002-2005 period are available at the state level but not at the county level. However, cropland cash rents are available by county for 2009. A two-step approach was used to calculate county cropland cash rental values for 2002-2005. First, the cropland cash rent ratios of a specific year to the available year, 2009, was computed. For example, if the state rental value was \$20 in 2008 and the county state rental value was \$30 in

2009, the ratio would be 0.66. The values for 2009, 2010, 2011, and 2012 were computed in similar way. Then, the average of the ratios across years was computed. In the second stage, the county land values for 2002 were computed by multiplying the ratio from first step times state cropland cash rental value for 2002. Insurance cost, operating interest, overhead, depreciation, interest, and THI (taxes, housing, interest) were included in the miscellaneous category. Efficiency scores were estimated for each of the 564 observations; four annual observations for each of 141 farms. Descriptive statistics of output and inputs, and factors affecting efficiency are summarized in table III-2 and III-3.

Empirical Results

Estimating Efficiency Score by Year and State

The average efficiency scores (table III-4) varied little across years. The average technical efficiency under variable returns to scale was 0.78. This score, 0.78, was greater than Mugera and Langemeier (2011) found for Kansas crop and livestock farms. They found an average score of 0.59 for data from 1993 to 2007. This difference might be attributed to the different number of outputs considered. Mugera and Langemeier included both crop and livestock, whereas this study includes only crops.

The average scale efficiency score for the current study was 0.92. This indicates that most of the farms operate close to optimal scale. Allocative and economic efficiency scores were low, 0.62 and 0.49, relative to technical efficiency. Precise causes for the low allocative and economic efficiency scores cannot be determined. One explanation is that the time gap between when inputs are required to be priced, purchased, and used, and when produced crops are priced and sold is relatively wide especially for a crop such as winter wheat.

Table III-5 shows the average technical, scale, allocative, and economic efficiency scores by state. Texas farms included in the survey had the highest technical, economic and scale efficiency with 0.87, 0.60 and 0.95 although their allocative efficiency was not the highest. Kansas farms had the highest allocative efficiency among states and the second highest technical and economic efficiency with 0.86 and 0.59. Statistical difference of efficiency score among states found to be significant based on the median and Wilcoxon test whose null hypothesis was that there was no mean difference of efficiency among the states. If the null is rejected, the efficiency scores are reported to be significantly different among the states. The differences of efficiency scores by state could result from at least two factors. One could be different amounts of inputs used by the producers and the other could be a consequence of different soil fertility and climate.

Distribution of Efficiency Scores

Figure III-2 shows the distribution of technical efficiency scores under variable returns to scale. Histogram was used to display for the distribution. Because efficiency scores were continuous, they were grouped by the ranges of score. 10 different ranges were grouped with interval 0.1. For example, if an efficiency score was 0.96, it fell in 1.Thirty-two percent of observations were technically efficient under variable returns to scales. The number of farms classified as technically inefficient were distributed relatively uniformly ranging from 0.5 to 0.9. About 19 percent of observations were fully efficient in scale but many of farms were close to fully efficient in scale. Although 81 percent of observations were not efficient, their scale efficiency scores were high. Most observations for allocative efficiency were located within the range from 0.6 to 0.8. The tail of the distribution is skewed to the left with more observations located below the average than above the average score. However, the distribution of economic efficiency shows that most observations were included in the range from 0.3 to 0.6 with a right skewed tail.

Efficiency Score by Farm Size and Crop Diversity

Farms included in the large size category were more technically efficient than farms in the very small, small, and medium categories (table III-6). This finding is consistent with that reported by Maugera and Langemeier (2011), Paul et al. (2004) and Weersink et al. (1990) who found that large farms were more technically efficient than farms in other size categories. Small farms had the most scale efficiency among the other size farms with an average value of 0.97. It appears that small farms could operate at optimal scale relative to large, small, and medium farms. This result is consistent with Byrnes (1987) who found that small Illinois grain farms were more scale efficient than large Illinois grain farms. Mugera and Langemeier (2011) also found that small farms included in their sample of Kansas farms were more scale efficient than farms of other sizes. Average economic and allocative efficiencies were the highest on large farms with respective values of 0.69 and 0.74. Thus, by these measures, large farms had relatively higher technical, allocative, and economic efficiency but relatively lower scale efficiency.

Table III-6 also includes average efficiency scores by crop diversity grouping. The wheat-only group had the highest average technical and scale efficiency scores, whereas the full diversity groups had the highest average allocative and economic efficiency scores. This finding is consistent with that reported by Mugera and Langemeir (2011) who found that crop farms were slightly more technically efficient than mixed farms that produced both crops and livestock.

Table III-7 includes average efficiency scores by combining farm size and level of diversity. Wheat-only farms among very small and small farms were significantly more technically efficient than some and full diversity farms, whereas wheat-only small and medium farms were less allocative efficient than some and full diversity farms. However, diversity did not differ among large farms

<u>Returns to Scale by Efficiency Score</u>

Following Varian (1980), returns to scale can be defined as follows. If some vector of input, x, produces some output, y, and all inputs are scaled by t, then if the production process exhibits constant returns to scale, output is also scaled by t. If this is not the case then by default the situation is characterized by variable returns to scale.

The frequency of observed values of returns to scale by farm size and state are reported in Table III-8. Eighty-one percent were operating in either decreasing or increasing returns to scale regions. Eighty-two percent of the observed large farms were operating in the decreasing returns to scale region. None of the large farms were in the increasing returns to scale category. Forty-five percent and five percent of small and very small farms were operating in the decreasing returns to scale region. Thirty-five and 73 percent of small and very small farm were in the increasing returns to scale category. Thus, most large farms were in the decreasing returns to scale category while most of the very small farms are in the increasing returns to scale category. This finding suggests that on average large farms could be too big to operate at optimal scale whereas the average small farms could be too small. This finding contrasts somewhat with that reported by Mugera and Langemeir (2011) who found that most of large farms in their sample were IRS. This difference could be related to differences of output definition. Their output included crops and livestock, whereas this study included only crops.

Table III-9 also shows categorization of returns to scale scores by state. A greater number of the Colorado, Kansas, and Oklahoma farms were in the decreasing returns to scale group than in the increasing returns to scale group. The opposite was the case for the Nebraska, Texas, and Wyoming farms.

<u>Possible Reduction of Inputs for Technical Inefficient Farm</u>

The possible reductions of inputs for inefficient farms were calculated using second stage linear programming. Table III-7 shows the quantity of reduction in input that the average inefficient farm could have implemented to achieve Koopmans's technical efficiency. Potential reduction in fertilizer expenditure was the highest at $22,000 per producer. Theoretically, chemicals could have been reduced by $12,000, machinery by $14,000, and seed by $6,000. Although land reduction was the highest, land is a semi-fixed asset and less liquid than the other inputs listed. The total average potential reduction across the 96 inefficient farms out of 141 farms in the sample is estimated to be $100,000 per year, with slack reduction of $34,000 and radial reduction of $66,000 based on average revenue of $221,016 with 2,690 acres cropped.

<u>Significant Factors Affecting Efficiency Through Tobit Random Effect Regression</u>

Regression results are presented in table III-10. The regression included year and state to account for weather, soil fertility, and other uncontrolled factors. Technical efficiency was significantly affected by size, crop diversity, number of cattle, percent of cash rented land, number of implements, and education. Technical efficiency was positively influenced by large farms. Large farms were technically more efficient than farms of other sizes which confirmed previous non parametric test.

The average wheat-only farm was more efficient than the average some diversity farm. The average technical efficiency score was reduced by crop diversification. Education and proportion of cash rented land to total cropland were positively related to technical efficiency, whereas number of cattle and number of implements were negatively related to technical efficiency. Size was the only statistically significant factor explaining scale efficiency. Small farms were more scale efficient than other sizes.

Allocative efficiency was affected by size, diversity, proportion of cash rented land, and custom work. On average, large farms contributed more to the allocative efficiency score than farms of other sizes and the farms in full diversity category contributed more than farms with less crop diversity. The proportion of cash rented land was positively related to allocative efficiency, whereas proportion of custom work was negatively related to allocative efficiency.

Economic efficiency was affected by farm size, number of cattle, tillage system, and by the proportion of cash rented land. Large farms contributed relatively the most to the economic efficiency score. The number of cattle was negatively related to the economic efficiency score, whereas proportion of cash rented land relative to cropland was positively related to economic efficiency. On average farms in the conventional tillage category were more economically efficient than farms in the no-till category.

Each of the estimated efficiency types was significantly affected by farm size. Large farms contributed the most to the average efficiency scores for technical, allocative, and economic efficiency but not for scale efficiency. Crop diversity affected technical efficiency negatively but allocative efficiency positively. The proportion of cash rented land relative to cropland affected technical, allocative, and economic efficiency positively. This finding is consistant with Olson and Vu (2006) and Langemeier and Bradford (2005).

Concluding Remarks

Our goal was to determine technical and economic efficiency of crop farms in the Western Great Plains and to find the source of inefficiency. Efficiency scores were calculated using DEA. The results show that technical, scale, allocation and economic inefficiency existed among the crop farms in the Western Great Plains. Average efficiencies of a crop farm were 0.78, 0.92, 0.68 and 0.49 for technical, scale, allocative, and economic efficiency, respectively. Thus, average of a crop farm in this region was lower allocative and economic efficiency compared to technical and scale efficiencies. It shows that allocative efficiency, which considers input quantities and prices, is important factor to improve efficiency. Efficiency score among the states were significantly different. Texas and Kansas farms were more efficient compared to other states, whereas Colorado and Wyoming farms were inefficient compared to other states.

In efficiency score by farm size, large farms were relatively more technically, allocatively, and economically efficient but relative less scale efficient than other sized farms. Small farms were efficient in scale. Wheat-only farms were more technically and scale efficient than some diversity farms, or full diversity farms but the wheat-only farms were less allocative, and economically efficient.

Based on the regression analysis, farm size greatly affected efficiency positively. In addition to size and crop diversity, number of cattle affected technical and economic efficiency negatively. Proportion of cash rented land relative to total cropland was related to technical, allocative, and economic efficiency positively. Number of power machine affected technical efficiency negetively and proportion of custom work affected allocative efficiency negatively. Education affected technical efficiency positively. The group of conventional tillage farms had higher economic efficient scores than farms in the no-till and minimum tillage group.

Therefore, the average farms in the sample were not efficient, meaning that they did not produce all crops with most efficient practices. Technically, based on the estimated models, the inefficient farms could produce the same amount of outputs with approximately half of their levels of input. The main sources of technical inefficiency for crop farms were small scale of operation, and low level of education. The regression with fallow not included in diversity variable was reported in the appendix for chapter 3.

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Table III-1. Models of efficiency measurement.

Efficiency	Model	Returns to scale	Estimating Efficiency	Interpretation
TECRS (model 1)	$\underset{\theta_i,\lambda_i}{\text{Min}}\ \theta_{i,\text{CRS}}$, Subject to $-y_i + Y\lambda \le 0 \quad i = 1,\ldots,n$ $\theta x_i - X\lambda \ge 0$ $\lambda \ge 0$,	Constant returns to scale (CRS)	$\theta_{i,CRS}$ (technical efficiency (TE) at CRS)	Estimate technical efficiency by minimizing inputs given outputs under CRS
TEVRS (model 2)	Model 1 plus $N\lambda = 1$	Variable returns to scale (VRS)	SE=TECRS/TEVRS=1, CRS SE=TECRS/TEVRS<1, VRS	Estimate technical efficiency by minimizing inputs given outputs under VRS and scale efficiency
NIRS (model 3)	Model 1 plus $N\lambda \le 1$	Non increasing returns to scale (NIRS)	SE=TENIRS/TECRS=1, IRS SE=TENIRS/TEVRS=1, DRS	Estimate NIRS for determining DRS or IRS
EEVRS (model 4)	$\underset{x_i^*,\lambda}{\text{Min}}\ w_i x_i^*$, Subject to $-y_i + Y\lambda \le 0$ $x_i^* - X\lambda \ge 0$ $N\lambda = 1$ $\lambda \ge 0$,		EEVRS = $w_i x_i^* / w_i x_i$	Estimate minimum cost given level of output produced at minimum cost Economic efficiency is the ratio of minimum cost to observed cost
AEVRS (model 5)			AEVRS= TEVRS/EEVRS	Estimate allocative efficiency by mixing input optimally at the lowest cost

Note: $\theta_{i,CRS}$ is a scalar variable for measuring technical efficiency under constant returns to scale, λ_i is weight variable for farm *i*, x_i is the actual quantity of *j*th input used by the ith farm, y_i is the actual quantity of crops produced by *i*th farm. N is an N X 1 vector of ones, w_i is the price of input *j*, x_i^* is minimum input requirement which is the solution of model 4. $w_i x_i^*$ is the minimum cost to produce given output at farm *i*, $w_i x_i$ is the actual cost of farm *i* used. TECRS is technical efficiency under CRS, TEVRS is technical efficiency under VRS, TENIRS is technical efficiency under non-increasing returns to scale, CRS denotes constant returns to scale, IRS denotes increasing returns to scale, DRS denotes decreasing returns to scale, SE denotes scale efficiency, EEVRS denotes economic efficiency under VRS, AEVRS denotes allocative efficiency under VRS.

Table III-2. Summary statistics of variables for computing efficiency score ($/farm/year).

Variables	Frequency[a]	Mean	Std. Dev.
Revenue	564	240,552	207,577
Machinery	564	36,811	34,748
Seeds	564	15,305	14,432
Fertilizer	468	33,396	39,243
Chemicals	496	21,484	40,965
Labor	560	6,165	4,962
Other	564	33,217	41,048
Land	564	62,501	55,634

[a] Estimates do not include zero values.

Table III-3. Summary statistics of variables for factors affecting efficiency

Variables	Definition	Mean	S. D.
Farm Size	Very small=0, small=1, medium=2, large=3	1.2	0.9
Diversity	Wheat only = 0, some diversity = 1, full diversity = 2	1	0.7
Cattle	Head of cattle	329	688
Type of Tillage	No till=0, minimum till=1, conventional till=2	1.2	0.68
Cash Leased Land	% of farm land cash leased	0.16	0.23
Power Machines	Number of power machines including tractors	4.7	2.36
Implement Machines	Number of implement machines attached to power machines	11.5	5.1
Proportion of Custom work	Ratio of number of custom work to total work	0.16	0.18
Age	Operator age in years	49.4	10.67
Education	Operator education in years	14.7	1.593
Family Tenure	Years in which the same family operated the farm	72.03	33.0
Off-farm Income	No=0, yes=1	0.72	0.45
Internet Use	Obtain producer-related information from the Internet yes=1, no=0	0.8	0.36
Number of Observations	544		

Table III-4. Technical (TEVRS), scale (SE), allocative (AEVRS) and economic (EEVRS) efficiency score by year .

	Number of Observations	TE VRS score	SE Score	AEVRS Score	EEVRS score
2002	141	0.82 (0.19)	0.92 (0.11)	0.67 (0.15)	0.55 (0.18)
2003	141	0.82 (0.18)	0.95 (0.08)	0.67 (0.14)	0.55 (0.18)
2004	141	0.78 (0.21)	0.94 (0.10)	0.61 (0.14)	0.48 (0.18)
2005	141	0.72 (0.22)	0.89 (0.12)	0.52 (0.18)	0.38 (0.20)
Mean	564	0.78 (0.20)	0.92 (0.10)	0.62 (0.11)	0.49 (0.20)

Notes: The number of observations is 564 because 141 producers have 4 observations for four years 2002-2005. The values in parentheses are standard deviations.

Table III-5. Technical (TEVRS), scale (SE), allocative (AEVRS) and economic (EEVRS) efficiency score by state.

	Number of Observations	TE VRS score	SE Score	AEVRS Score	EEVRS score
Colorado	140	0.72 (0.20)	0.89 (0.13)	0.57 (0.15)	0.41 (0.18)
Kansas	48	0.86 (0.15)	0.92 (0.09)	0.69 (0.15)	0.59 (0.16)
Nebraska	56	0.71 (0.23)	0.95 (0.08)	0.62 (0.14)	0.42 (0.14)
Oklahoma	168	0.81 (0.19)	0.93 (0.11)	0.60 (0.16)	0.49 (0.20)
Texas	96	0.87 (0.17)	0.95 (0.08)	0.68 (0.16)	0.60 (0.21)
Wyoming	56	0.72 (0.22)	0.93 (0.11)	0.67 (0.32)	0.47 (0.20)

Notes: The number of observations is 564 because 141 producers have 4 observations for four years 2002-2005. The values in parentheses are standard deviations.

Table III-6. Technical (TEVRS), scale (SE), allocative (AEVRS) and economic efficiency (EEVRS) score under variable returns to scale by farm size and crop diversity.

	Farm Size[a]				
	Number of Observations	TEVRS	SE	AEVRS	EEVRS
Very Small	139	0.78 (0.22)	0.90 (0.14)	0.60 (0.17)	0.47 (0.21)
Small	224	0.75 (0.21)	0.97 (0.05)	0.59 (0.16)	0.44 (0.17)
Medium	151	0.80 (0.18)	0.92 (0.10)	0.64 (0.15)	0.51 (0.18)
Large	50	0.92 (0.13)	0.83 (0.15)	0.74 (0.17)	0.69 (0.21)
Mean	564	0.78 (0.20)	0.92 (0.11)	0.62 (0.16)	0.49 (0.20)
	Crop Diversity[b]				
	Number of Observations	TEVRS	SE	AEVRS	EEVRS
Wheat-only	140	0.82 (0.19)	0.93 (0.10)	0.57 (0.15)	0.47 (0.18)
Some Diversity	284	0.76 (0.20)	0.93 (0.12)	0.61 (0.17)	0.47 (0.20)
Full Diversity	140	0.80 (0.21)	0.92 (0.10)	0.69 (0.15)	0.55 (0.21)
Mean	564	0.78 (0.20)	0.92 (0.11)	0.62 (0.16)	0.49 (0.20)

[a]Farm size was classified by total revenue. Large farms were greater than $500,000 of their revenue, medium farms were $250,000 ~ $500,000, small farms were $100,000~ $250,000, and very small farms were less than $100,000.

[b]Crop diversity was classified based on the ratio of the area of wheat and fallow to total land cropped. Farms that fell in the upper 25% of the diversity ratio were classified as wheat-only. Farms that fell in the lower 25% of the diversity ratio were classified as full diversity. Those farms in the middle 50% were classified as some diversity.

Notes: The number of observations is 564 because 141 producers have 4 observations for four years 2002-2005.
Values in parentheses are standard deviations.

Table III-7. Technical, scale, allocative and economic efficiency score under variable returns to scale by combining farm size and crop diversity

	Crop Diversity[b]		
	Technical Efficiency Under Variable Returns to Scale		
Farm Size[a]	Wheat only	Some diversity	Full diversity
Very Small	0.82 (0.20)*	0.72 (0.22)	0.78 (0.22)
Small	0.81 (0.21)*	0.74 (0.20)	0.75 (0.21)
Medium	0.82 (0.18)	0.78 (0.17)	0.80 (0.18)
Large	0.93 (0.08)	0.91 (0.14)	0.92 (0.13)
	Scale Efficiency		
Very Small	0.88 (0.14)	0.91 (0.13)	0.88 (0.14)
Small	0.97 (0.05)	0.97 (0.05)	0.97 (0.05)
Medium	0.92 (0.09)	0.92 (0.11)	0.93 (0.08)
Large	0.84 (0.16)	0.80 (0.18)	0.85 (0.11)
	Allocative Efficiency Under Variable Returns to Scale		
Very Small	0.56 (0.16)	0.61 (0.18)	0.65 (0.18)
Small	0.56 (0.15)	0.58 (0.16)	0.66 (0.14)*
Medium	0.59 (0.13)	0.60 (0.14)	0.73 (0.13)*
Large	0.62 (0.16)	0.78 (0.18)	0.74 (0.13)
	Economic Efficiency Under Variable Returns to Scale		
Very Small	0.48 (0.21)	0.44 (0.20)	0.54 (0.22)
Small	0.45 (0.16)	0.43 (0.17)	0.46 (0.18)
Medium	0.48 (0.15)	0.47 (0.16)	0.61 (0.20)
Large	0.58 (0.18)	0.72 (0.23)	0.69 (0.17)

[a]Farm size was classified by total revenue. Large farms were greater than $500,000 of their revenue, medium farms were $250,000 ~ $500,000, small farms were $100,000~ $250,000, and very small farms were less than $100,000.

[b]Crop diversity was classified based on the ratio of the area of wheat and fallow to total land cropped. Farms that fell in the upper 25% of the diversity ratio were classified as wheat-only. Farms that fell in the lower 25% of the diversity ratio were classified as full diversity. Those farms in the middle 50% were classified as some diversity.

Notes: * indicates significantly different among columns at 5% level based on Median and Willcoxon test.
Values in parentheses are standard deviations

Table III-8. Frequency of returns to scale by farm size and state

	CRS[b]	DRS	IRS	Total
	Farm Size[a]			
Very small	31	7	101	139
Small	42	103	79	224
Medium	27	110	14	151
Large	9	41	-	50
Total	109	261	194	564
	State			
Colorado	14	73	53	140
Kansas	9	30	9	48
Nebraska	11	20	25	56
Oklahoma	36	89	43	168
Texas	31	28	37	96
Wyoming	8	21	27	56
Total	109	261	194	564

[a]Farm size was classified by total revenue. Large farms were greater than $500,000 of their revenue, medium farms were $250,000 ~ $500,000, small farms were $100,000~ $250,000, and very small farms were less than $100,000.

[b]CRS represents constant returns to scale, DRS represent decreasing returns to scale, and IRS represent increasing returns to scale. To determine returns to scale, if scale efficiency is one, a farm is on constant returns to scale (CRS); if scale efficiency is less than one and the score of non increasing retursn to scale is the same as TECRS score, the farm operates under IRS. Otherwise, the producer operates under DRS.

Table III-9. Average reduction of inputs[a] for achieving the highest TEVRS for inefficency farms ($/producer)

Input	Average Input Used	Slack Reduction	Radial Reduction	Total Reduction	Percent of Each Input Reduction (%)
Machinery	36,682	3,212	11,049	14,261	39
Seeds	15,573	1,567	4,907	6,474	42
Fertilizer	34,732	11,545	10,632	22,177	64
Chemicals	21,673	5,458	6,807	12,265	57
Labor	6,269	734	1,966	2,700	43
Miscellaneous	32,779	3,809	10,257	14,065	43
Land	63,707	8,213	20,209	28,422	45
Total	211,379	34,537	65,827	100,363	47

Note: The number of farms is 96 out of 141 farms which were technically inefficient in 2002-2005. Average reduction of inputs to achieve the highest technical efficiency under variable returns to scale were based on average revenue $221,016 with 2,690 acres cropped.

Table III-10. Relationships between efficiency and farm characteristics using Tobit random effect model

Variable	Technical		Scale		Allocative		Economic	
Intercept	0.009	***	1.01	***	0.08	***	0.49	
Year								
2003	-0.04	**	0.04	***	0.023	***	-0.034	**
2004	-0.08	***	0.03	***	0.07	***	-0.093	***
2005	-0.18	***	-0.21	*	-0.17	*	-0.21	***
State								
Colorado	-0.07		-0.01		-0.13	**	-0.13	***
Kansas	0.02		0.02		-0.10	**	-0.05	
Nebraska	.019		0.04		-0.07	*	-0.06	
Oklahoma	-0.03		0.02		-0.14	***	-0.12	***
Texas	0.13	**	0.06	**	-0.01		0.08	**
Farm Size								
Small	-0.00		0.06	***	0.01		0.002	
Medium	0.14	***	0.02		0.07	***	0.12	***
Large	0.38	***	-0.06	**	0.18	***	0.32	***
Crop Diversity								
Some diversity	-.074	*	-0.01		0.3		-0.011	
Full diversity	-.028		0.00		0.08	***	0.05	
Number of Head Cows	-.005	**	-0.00		-0.00		-0.003	**
Tillage								
Minimum	0.02		-.015		-0.001		.01	
Conventional	0.09		.017		0.03		0.07	*
Proportion of Farm Land Cash Rented	0.22	***	-.012		0.07	*	0.16	***
Number of Implement Machines	-0.01		0.00		0.003		-0.0009	
Number of Power Machines	0.006	*	-0.01		-0.008		-0.007	
Proportion of Custom Work	0.05		0.01		-0.123	***	-0.065	
Age	0.002		-0.00		-0.001		-0.005	
Education	0.025	**	-0.01		-0.002		0.009	
Family Tenure	-0.0007		-0.01		0.000		-0.0002	
Off-farm Income No	0.02		0.00		-0.023		0.0004	
Internet Use No	-0.08		0.01		-0.00		-0.028	
Number of Obs.	544							

Notes: Single, double, and triple asterisk (*) denote significance at the 10%, 5% and 1% levels. Discrete variables of omission were 2002 in year, Wyoming in state, very small in size, wheat only in diversity, no-till in tillage, Yes in off-farm income, and Yes in intern use.

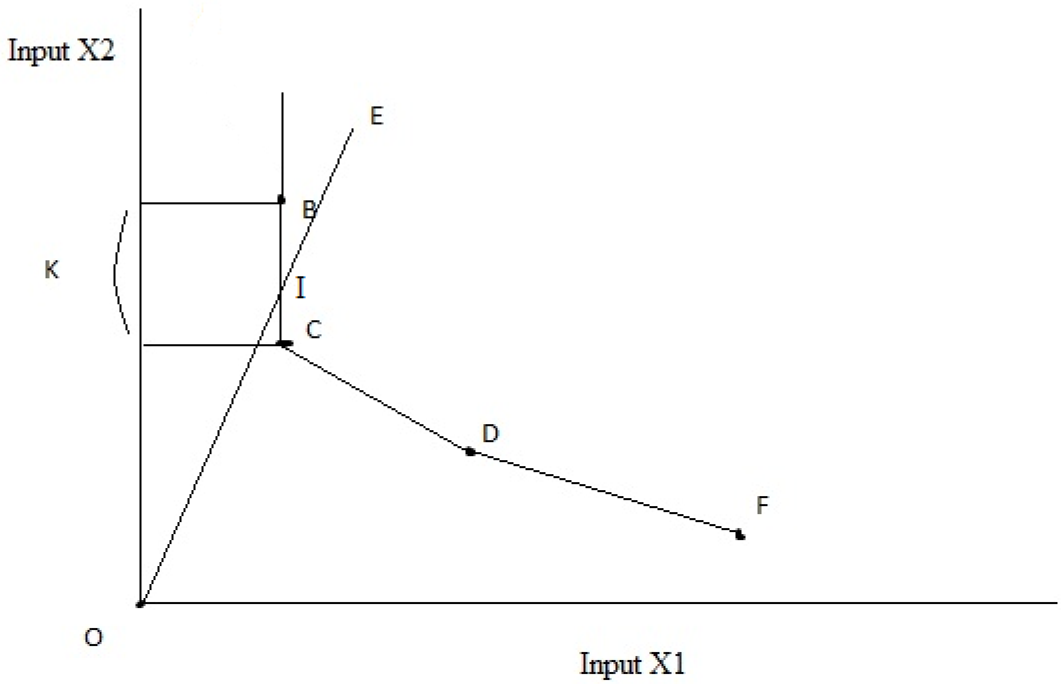

Figure III-1. Slack and radial input reduction for technical inefficient farms

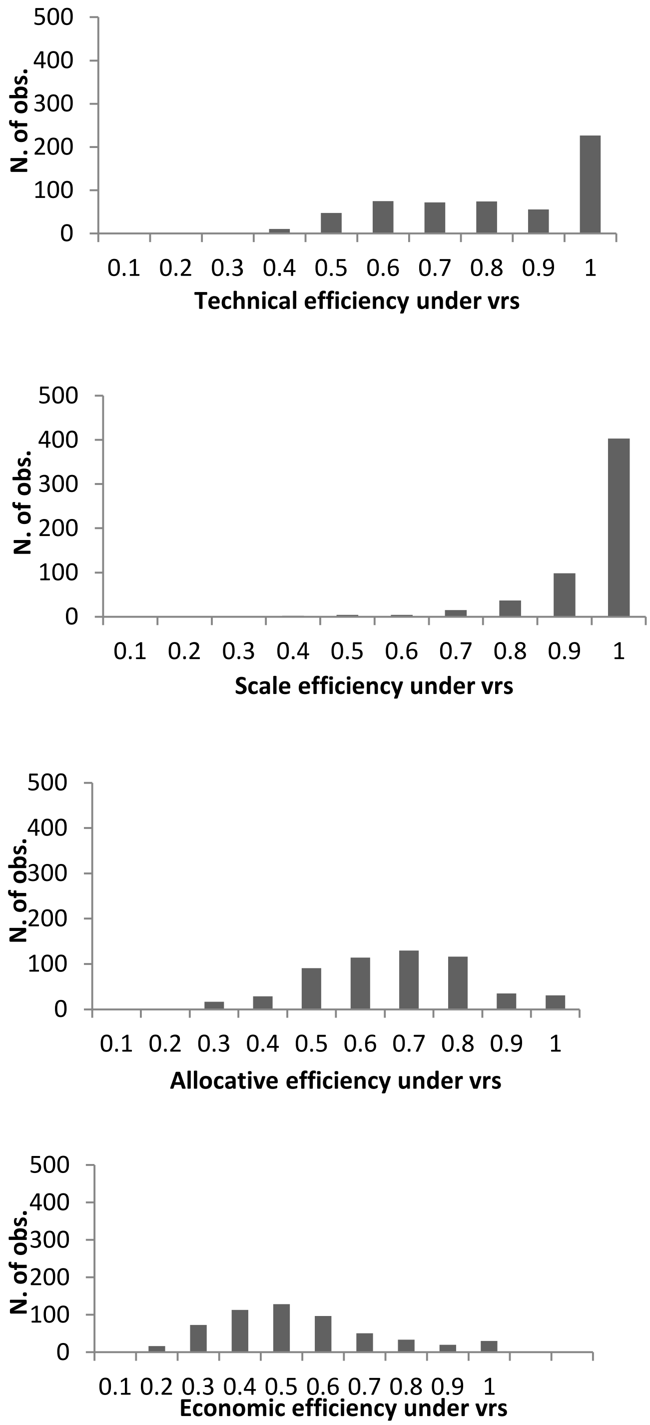

Figure III-2. Distribution of the score of technical, scale, allocative, and economic efficiency under variable returns to scale

Appendix for Chapter III

Table III-11. Relationships between efficiency and farm characteristics using Tobit random effect model with fallow not included in diversity variable.

Variable	Technical		Scale		Allocative		Economic	
Intercept	0.50	**	1.00	***	0.8	***	0.48	***
Year								
2003	-0.04	*	0.04	***	0.023	***	-0.034	**
2004	-0.08	***	0.03	**	0.07	***	-0.093	***
2005	-0.18	***	-0.21	*	-0.17	*	-0.21	***
State								
Colorado	-0.08		-0.02		-0.14	**	-0.13	***
Kansas	0.05		0.02		-0.09	**	-0.04	
Nebraska	0.02		0.04		-0.07	*	-0.07	
Oklahoma	-0.04		0.01		-0.14	***	-0.12	***
Texas	0.13	**	0.06	**	-0.01		0.07	*
Farm Size								
Small	-0.00		0.06	***	0.01		0.002	
Medium	0.14	***	0.02		0.07	***	0.12	***
Large	0.38	***	-0.06	**	0.18	***	0.32	***
Crop Diversity								
Some diversity	-.079		-0.01		0.01		-0.03	
Full diversity	-.017		-0.00		0.07	**	0.03	
Number of Head Cows	-.005	**	-0.00		-0.00		-0.003	**
Tillage								
Minimum	0.02		-.015		-0.001		0.01	
Conventional	0.08		.016		0.03		0.06	
Proportion of Farm Land Cash Rented	0.24	***	-.013		0.07	*	0.16	***
Number of Implement Machines	-0.01*		0.00		0.004		-0.0007	
Number of Power Machines	0.005		-0.01		-0.008		-0.005	
Proportion of Custom Work	0.04		0.01		-0.105	**	-0.055	
Age	0.002		-0.00		-0.002*		-0.0006	
Education	0.027	**	-0.00		-0.001		0.01	
Family Tenure	-0.0006		-0.00		0.000		0.00	
Off-farm Income No	0.01		0.001		-0.022		-0.003	
Internet Use No	-0.08*		0.01		-0.00		-0.03	
Number of Obs.	544							

Note: The criterion of diversity was defined as $\frac{\text{wheat acres}}{\text{total cropped acres}}$. Fallow net returns were allocated across crops according to the harvested crop acres in each year. Some fallow acres received revenue from government payments. Some fallow acres incurred costs for activities such as tillage, herbicide application and custom work.

CHAPTER IV

NONPARAMETRIC AND PARAMETRIC METHODS FOR MEASURING FARM EFFICIENCY

Abstract

The objective of the research reported in this chapter is to determine farm and producer characteristics that are associated with efficient production with efficiency estimated by both data envelopment analysis (DEA) and stochastic frontier analysis (SFA). Data were obtained from 141 crop farms in the Western Great Plains for each of four years, 2002 to 2005. Four DEA and five SFA estimation methods were used. The Spearman rank-order correlation of technical efficiency between DEA and SFA approaches ranged from 0.45 to 0.53. Both approaches found that the average farm in the sample operated under decreasing returns to scale and that farm size significantly affected technical efficiencies. Thus, the two approaches produced different estimates for technical efficiency scores, but gave similar results for returns to scale, and for determining factors affecting efficiency.

Introduction

For decades agricultural economists have sought means for identifying efficient farms and for differentiating among the characteristics of efficient and inefficient farms. In a seminal paper, Ferrell (1957) explained why measurement of production efficiency is important. He defined technically efficient firms as those that produce on the production frontier. He defined allocatively efficient firms as those that not only produce on the frontier but also combine inputs in a manner so that the value of their marginal product is equated with their market price

Measuring efficiency across farms and determining the significant factors affecting performance is critical to identifying characteristics of efficient farms.

Researchers have developed several methods for computing empirical estimates of efficiency. No single method has been found to be unambiguously superior. Some researchers use the nonparametric data envelopment analysis (DEA) method, and others use a parametric method, stochastic frontier analysis (SFA).

Charnes et al. (1978) developed a linear programming method for DEA. Banker et al. (1984) incorporated returns to scale into DEA. The DEA method can be used to determine what is known as scale efficiency which is a test of the firm's scale relative to an optimal scale. The DEA method has been extended by improving the process for incorporating statistical properties using bootstrapping (Simar and Wilson 1998) enabling testing statistical significance of efficiency scores (Banker et al. 2010). In general, the DEA method estimates efficiency as the ratio of the sum of weighted outputs to the sum of weighted inputs. Advantages of the DEA method is that it can accommodate multiple outputs and multiple inputs and that a functional form specification is not required. A disadvantage is that it does not acknowledge noise in the data. Noise becomes part of the efficiency score. Hence, DEA is sensitive to outliers and attributes all of the deviation from an efficient frontier as inefficiency.

Aigner and Chu (1968) differentiated a frontier production function from an average production function by introducing proxy variables for describing the technical level of firms from the traditional average production function. They estimated the frontier function using econometric and linear programming methods. Aigner et al. (1977) developed SFA along with Meeusen and Broeck (1977) based on Ferrell's efficiency concept in which inefficiency is defined as a deviation from the frontier of the production frontier. The SFA method decomposes error into two components, an inefficiency term and a random error term. Aigner et al. (1977) assumed that inefficiency is distributed half normal and exponential, whereas, Meeusen and

Broeck (1977) assumed that inefficiency is distributed as exponential. Both sets of researchers estimated inefficiency using maximum likelihood.

Greene (1990) formulated a model with inefficiency captured by a gamma distribution. Pitt and Lee (1981) used panel data that enabled the testing of a firm's behavior with repeated time rather than one time (cross sectional data). They used a random effect model for panel data assumed inefficiency effect distributed with constant mean and variance but is not correlated with regressors. Battese and Coelli (1992) extended the Pitt and Lee (1981) time invariant efficiency approach to a time variant model. Cornwell et al.(1990) used a fixed effects method for estimating inefficiency which was distribution free ('fixed') but allowed to be correlated with regressors. But, their efficiency was time invariant. Greene (2004a, 2004b, 2005) explained that efficiency with the time invariant approach could include not only an inefficiency effect but also a heterogeneity effect such as different characteristics of firms. He suggested a true fixed and random effects model which excluded the heterogeneity effect from the inefficiency effect in the Cornwell et al. (1990)'s fixed and Pitt and Lee (1981)'s random effects model

Farsi et al. (2005) applied Greene's true random effects model to Swiss railway company data. They found that the true random effects model reduced correlation between heterogeneity and inefficiency by reducing the inefficiency effect compared to the Pitt and Lee (1981) and Cornwell et al. (1984) methods. Farsi et al. (2006) applied Greene's true fixed effects model to electricity distribution data. They found that Greene's method accounted for heterogeneity of the sector and gave another option to explain inefficiency compared to the traditional SFA model.

In general, the SFA method measures inefficiency by estimating the mean of output, a one-sided error which accounts for the inefficiency effect, and a two sided random error which accounts for random shock and measurement error. The advantage of the SFA method is that it allows for measurement error and for random shocks in the production function, whereas the disadvantage is that it is sensitive to the form of production function selected and to the distribution assumed for the inefficiency effect.

Because of the advantages and disadvantages of DEA and SFA, neither method has emerged as the superior approach. Coelli et al. (2003) stated that if the data include considerable random errors such as with agricultural production data from developing countries, it could be better to use SFA. Otherwise, DEA could be a better choice. Several researches have compared the two methods (Kalaitzandonakes et al. 1991, Hjalmarsson et al. 1996, Murova et al. 2004, Mo 2009). Most of these studies have found that estimating efficiency using both of the methods have produced different results. Some studies have found strong correlation between the two methods, whereas others have found weak correlation.

Kalaitzandonakes et al. (1992) found that technical efficiency scores estimated by DEA were 11% greater than those estimated by SFA for Illinois grain farms. They also found that DEA technical efficiency scores did not differ across farm size, whereas SFA scores significantly differed across farm size. Murova et al. (2004) found that DEA scores were 7% greater than those of SFA among 25 agricultural states in Ukraine. Hjalmarsson et al. (1996) studied data of Colombian cement factories. They found that DEA mean technical efficiency scores, under variable returns to scale, were 2% higher than that estimated by SFA. Mo (2009) found that the parametric efficiency estimates for both scale and economic efficiency were greater than the nonparametric estimates for Kansas wheat farms and that the efficiency scores varied from year to year. Ray et al. (1995) evaluated data from 123 electric utilities and found that DEA technical efficiency scores were not significantly higher than SFA scores based on the Wilcoxon signed-rank sum test.

Greene (2004a, 2004b, 2005) suggested a true fixed and a random effects model which separates the firm specific effect from the inefficiency effect. However, no prior research has compared SFA and DEA with the recent advanced SFA techniques for crop farms. Nor have many researchers compared the correlation of scale efficiency between the two methods except for Hjalmarsson et al. (1996) who found that the mean scale efficiencies were similar among SFA, DEA and deterministic frontier analysis, and Forsund (1992) who found that the correlation of scale efficiency between deterministic frontier analysis and DEA was 0.74 using data from Norweigan ferries.

The objective of the research reported in this chapter is to compare efficiency estimated by DEA and SFA and to determine farm and producer characteristics that are associated with efficient production. Nine different methods, including both parametric and nonparametric approaches, are used to compute estimates of technical and scale efficiency. Technical efficiency scores are evaluated to determine farm and producer characteristics that significantly affect farm production efficiency. The study evaluates empirical data obtained from each of four crop production years from 141 farms across six states in the Western Great Plains.

The Conceptual Framework

The study is designed to measure technical and scale efficiency and to determine which factors affect technical efficiency. Both output oriented DEA and SFA methods are used to compute efficiency scores.

<u>Nonparametric Method: Data Envelopment Analysis (DEA)</u>

Following Banker et al. (1984), output oriented technical efficiency, which maximizes output given levels of inputs under assumed variable returns to scale, is defined:

$$\begin{aligned} &\underset{\varphi_i,\lambda}{\mathrm{Max}}\frac{1}{\varphi_i} \\ &\lambda\mathbf{Y} \le \frac{1}{\varphi}\mathbf{y} \\ &\lambda\mathbf{X} \ge \mathbf{x}, \\ &\mathrm{N}\lambda = 1 \end{aligned} \tag{4.1}$$

where **Y** is a vector of outputs for all farms, **y** is a vector of output from the farm to be tested, **X** is a matrix of inputs for all farms, **x** is a vector of inputs used by a testing farm, λ is weight variable, φ_i is the measure of technical efficiency for a testing farm with $\frac{1}{\varphi_i}$ bounded to be from zero to one. N is a vector of ones. For calculating technical efficiency under variable returns to scale, a constraint to require the sum of λ across all farms to be equal to one, is added to the model. The first constraint requires that the farm being evaluated (the test farm) produce output equal to that of the farm(s) on the efficient frontier. The second constraint requires that the farm being evaluated uses as much input as farm(s) on the efficient frontier. The third constraint is a convex combination constraint in that the sum of lambdas across all farms is required to be equal to one under variable returns to scale implying that the frontier is a convex envelope. The equation (4.1) solved an efficiency score of each farm. For N farms, it needs N times to solve. Efficiency score little varied by year based on equation (4.1).

For comparing SFA and DEA to measure technical efficiency, four different techniques of DEA are considered (Hjalmarsson 1996, Cummins and Zi 1998, Bauer et al. 1998). They are:

1) DEAVP: a technical efficiency score under variable returns to scale with total observations (564) that includes four annual observations for each of the 141 farms;

2) DEAVC: a technical efficiency score under constant returns to scale with total observations;

3) DEAVS: a technical efficiency score under variable returns to scale by annual observations, with a reference set of 141 observations separated by year. It was solved four times because the data had four years observation for 141 farms. It means that the efficiency scores were calculated each year separately.

4) DEACS: a technical efficiency score under constant returns to scale by annual observations.

Scale efficiency estimated by DEA is defined as the ratio of technical efficiency under constant returns to scale to technical efficiency under variable returns to scale. If this ratio is one, a farm is scale efficient which implies constant returns to scale (CRS). If the scale efficiency score is less than one, a farm is scale inefficient. If a farm is scale inefficient, it could be a result of operating in the increasing returns to scale (IRS) zone or in the decreasing returns to scale (DRS) zone. To determine if the nonscale efficient firm is either increasing returns to scale or decreasing returns to scale, an additional linear programming problem was solved. It is referred to as the non-increasing returns to scale (NIRS) model.

The NIRS model augments equation (4.1) by adding a constraint requiring that the sum of the lambdas is less than one. If the non-increasing returns to scale NIRS score is the same as that of the technical efficiency under constant returns to scale, the firm is said to be operating in an increasing returns to scale zone. Otherwise, the firm is said to be operating in the decreasing returns to scale zone. GAMS software(GAMS Development Corporation 2009) was used to estimate DEA technical and scale efficiency scores for each farm.

<u>Parametric Method: Stochastic Frontier Analysis (SFA)</u>

The stochastic frontier production function is defined as:

$$Y_{it} = X_{it}\beta - u_{it} + v_{it}\,, \tag{4.2}$$

where Y_{it} is a vector of logged output at farm i year t, X_{it} is a matrix of logged inputs at farm i year t, β is a vector of parameters to be estimated, u_{it} is a one-side error and positive, which accounts for the inefficiency effect. Generally, it is assumed to be a half normal or a truncated normal distribution. In this study, a half normal distribution was assumed. v_{it} is a symmetric random error distributed normally with mean 0 and constant variance. u_{it} and v_{it} are assumed to be independent. Thus, output oriented technical efficiency is defined as:

$$\mathrm{TE}_{\mathrm{it}} = \frac{f(X_{it};\beta)\exp(v_{\mathrm{it}})\exp(-u_{it})}{f(X_{it};\beta)\exp(v_{\mathrm{it}})} = \exp(-u_{it}) \tag{4.3}$$

Technical efficiency is the ratio of the observed output for farm i (the test farm), relative to the frontier function, given the input vector X_{it}.

Five SFA techniques were used to estimate the stochastic frontier production function given the panel data setting (Hjalmarsson et al. 1996, Giannakas et al. 2001, Murova et al. 2004). They are the following:

1) SFA1 following Pitt and Lee (1981) and Battese and Coelli (1992), is a random effects model with time invariant technical efficiency, implying technical efficiency dose not vary over time.

2) SFA2 following Cornwell et al. (1990), is a deterministic frontier model estimated by a fixed effects model which does not need to assume a distribution for the inefficiency effect, nor assume the independence of production or shifting factors variable and inefficiency effect.

3) SFA3 following Battese and Coelli (1992, 1995) is the same as SFA1 except allowing for technical efficiency to vary over time;

4) SFA4 and SFA5 are true fixed and a random effects models which are similar to SFA1 and SFA3, respectively, but overcome the disadvantage of the time invariant effect being included in the inefficiency effects. These formulations are consistent with recommendations by Greene (2004a, 2004b, 2005). The technical efficiency of SFA4 and SFA5 are allowed to vary over time. Returns to scale (RTS) (scale efficiency in DEA) was calculated by summing the elasticities of each input. The elasticity of each input was calculated by taking the first order derivative of equation (4.2) with respect to each input:

SFA1 and SFA3

Following Battese and Coelli (1992, 1995), a translog production frontier function SFA1 model is defined as:

$$y_{it} = \alpha + \sum_{j=1} \delta_j \, x_{jit} + \sum_{j=1} \sum_{k=1} \beta_{jk} x_{jit} x_{kit} + v_{it} - u_{it} \tag{4.4}$$

where y_{it} is logged output at farm i, year t, x_{jit} is logged input j, v_{it} is a symmetric error term normally distributed with mean 0 and constant variance, u_{it} is a non-negative variable distributed half normal with mean zero and constant variance used to account for the inefficiency effects, and v_{it} and u_{it} are independent .

Because SFA1 is time invariant, it can be specified as $u_{it} = u_i$. The concept of a time invariant inefficiency effect is different from the concept of including a year variable in the production function. A time invariant inefficiency effect means the inefficiency effect does not differ over the time period, whereas including year variables in the production function could theoretically account for year-to-year technical efficiency change. According to Coelli (2003), this discrimination is only possible when the inefficiency effect is stochastic and has a specific distribution. The year variable can be included as an exogenous variable to determine factor efficiency effects. In which case, different years are permitted to affect efficiency differently. To estimate equation (4.4), Battese and Coelli (1992) used the following log likelihood function:

$$\text{Ln L}(\theta; \text{y}) = -\frac{1}{2}(\sum_{i=1}^{N} T_i)\{\ln(2\pi) + \ln\sigma_s^2 - \frac{1}{2}\sum_{i=1}^{N}(T_i - 1)\ln(1-\gamma) - \frac{1}{2}\sum_{i=1}^{N} T_i \tag{4.5}$$

$$\ln[1 + \eta_i^{'}\eta_i - 1)\gamma] - N\ln[1 - \Phi(Z)] - \frac{1}{2}NZ^2 + \sum_{i=1}^{N}\ln[1 - \Phi(-Z_i^*)]$$

$$+\frac{1}{2}\sum_{i=1}^{N}(y_i - x_i\beta)'(y_i - x_i\beta)/(1-\gamma)\sigma_s^2$$

where $\theta = (\beta', \sigma_s^2, \gamma, \mu, \eta)$, $z = \dfrac{\mu}{(\gamma\sigma_s^2)^{\frac{1}{2}}}$ and $z_i^* = \dfrac{\mu(1-\gamma) - \gamma\eta_i^{'}(y_i - x_i\beta)}{\{\gamma(1-\gamma)\sigma_s^2[1 + \eta_i^{'}\eta_i - 1)\gamma]\}^{1/2}}$. $\gamma = \dfrac{\sigma^2}{\sigma_s^2}$ and

$\sigma_v^2 + \sigma^2 = \sigma_s^2$ where σ^2 is a variance of one side error term and , σ_s^2 is a variance ofresidual of ordinary least square, Φ is the distribution function of the cumulative normal random variables, Minimizing log likelinood function gives estimates of the parameters $\beta, \sigma^2, \sigma_v^2$. Based on these parameters, the conditional distribution f(u_i| ε_i) can be calculated where ε_i is the residual of the ordinary least squares estimate. Either the mean or the mode of f (u_i| ε_i) can be used for calculating each farm's technical efficiency by calculating

$$\text{TE}_i = \text{E}(\exp\ (-u_i)|\ \varepsilon_i\ ), \tag{4.6}$$

where TE_i is technical efficiency at farm *i*, E() is expectation, exp() is exponential function. SFA3 is the same as SFA1 except that it includes the time varying parameter, eta η as an inefficiency variable, which allows efficiency to vary over time. Thus the production function for SFA3 is specified as equation (4.5) plus the following

$$u_{it} = \{\exp[-\eta(t - T)]\}u_i, \tag{4.7}$$

where t is the time variable, t = 1 to T, u_i is a variable of inefficiency effect, and η is a time parameter to be estimated. If η is negative, technical inefficiency is decreasing over time. If η is positive, technical inefficiency is increasing over time. If the estimated parameter value is zero, technical inefficiency is constant over time.

Returns to scale (RTS) (scale efficiency in DEA) of SFA1 and SFA3 was calculated by summing the elasticities of each input. The elasticity of each input was calculated by taking the first order derivative of equation (4.4) with respect to each input:

$$\mathrm{RTS} = \frac{\partial y_{it}}{\partial X_{jit}} = \sum_j \beta_j x_j + \delta , \tag{4.8}$$

where the value of x_j is generally used as the mean of input j observation. The following equation was used to find significant factors affecting efficiency for SFA1 and SFA3:

$$u_{it} = \alpha + \beta z_{it} , \tag{4.9}$$

where u_{it} is a one side disturbance term from the production function, is distributed by truncation of the $N(u_{it}, \sigma^2)$, which is a nonnegative disturbance capturing the inefficiency effect, z_{it} includes demographic and economic variables.

Equations (4.5), (4.7) and (4.9) are estimated simultaneously using maximum likelihood. The estimation method has an advantage in that it does not have an omitted variables problem and does not violate the independence assumption that z_{it} is independent of x_{it}, criticisms leveled at the two-step approach. FRONTIER version 0.997-14 (Coelli and Henningsen 2012) was used for estimating SFA1. The measure of efficiency of SFA is the value of the output of i-th farm relative to the maximum output of unobserved fully efficient farm using the same input vector. Whereas the measure of efficiency of DEA is the value of the output of i-th farm relative to the value output of observed fully efficiency farm.

SFA2

SFA2 is a deterministic stochastic frontier production function which means the inefficiency effect is fixed. It does not allow for random shocks such as a high number of random equipment failures, bad weather, or any error or imperfection in the specification of the model or measurement in its component variables. The model specification is defined as

$$\begin{aligned} y_{it} &= \alpha_{\mathrm{i}} + \sum_{j=1}\delta_j x_{jit} + \frac{1}{2}\sum_{j=1}\sum_{k=1}\beta_{jk} x_{jit} x_{kit} + v_{it} \\ &= \max(\alpha_i) + \sum_{j=1}\delta_j x_{jit} + \frac{1}{2}\sum_{j=1}\sum_{k=1}\beta_{jk} x_{jit} x_{kit} + v_{it} + [\alpha_{\mathrm{i}} - \max(\alpha_i)] \\ &= \alpha + \sum_{j=1}\delta_j x_{jit} + \frac{1}{2}\sum_{j=1}\sum_{k=1}\beta_{jk} x_{jit} x_{kit} + v_{it} - u_i \end{aligned} \tag{4.10}$$

where $\mathrm{u}_i = \max(\alpha_i) - \alpha_{\mathrm{i}} > 0$, other symbols were defined in equation (4.5). SFA2 is a fixed effects approach which is a traditional estimation method for panel data. Estimating this equation required two steps. In the first step, the intercepts and slopes of parameters δ and β_k are estimated using OLS because OLS estimates remain unbiased and best linear smaller variance without normality assumption. In the second step, technical efficiency (TE$_i$) for farm *i* is estimated by equation (4.11).

$$\mathrm{TE}_i = \hat{\alpha}_i - \max(\hat{\alpha}_j), \tag{4.11}$$

where $\hat{\alpha}_i$ is intercept of farm *i* estimated by equation (4.10) and $\max(\hat{\alpha}_j)$ is the maximum intercept value from among all intercepts estimated for all firms in the data set.

SFA2 has an advantage in that a distribution function assumption is not required for the inefficiency variables, and it allows input variables to be correlated with inefficiency effect or random disturbance. However, its disadvantage is that the inefficiency effect includes the time invariant effect which does not belong to the inefficiency effect. This is a corrected ordinary least squares method which uses a traditional panel data fixed effects model.

SFA4 and SFA5

Greene (2004a, 2004b, 2005) suggested a true fixed effects and a random effects model (SFA4, SFA5) to overcome the limitations of SFA1 and SFA2. The main difference of SFA4 and SFA5 from the previous models is to exclude the time invariant effect from the inefficiency effect by adding unobservable farm specific factors. A true fixed effects model is specified:

$$y_{it} = \alpha_i + \sum_{j=1} \delta_j x_{jit} + \frac{1}{2}\sum_{j=1}\sum_{k=1} \beta_{jk} x_{jit} x_{kit} + v_{it} - u_{it}, \tag{4.12}$$

where α_i is farm specific effect and u_{it} is the inefficiency effect varying over time. u_{it} is distributed with a half normal i.e. $|N(0,\sigma_u^2)|$, and v_{it} is distributed with normal i.e. $N(0.\sigma_v^2)$ Equation (4.12) can be estimated using maximum likelihood estimation. The FRONTIER command of LIMDEP was used for estimation.

A true random effects model is specified:

$$y_{it} = \alpha + w_i + \sum_{j=1} \delta_j x_{jit} + \frac{1}{2}\sum_{j=1}\sum_{k=1} \beta_{jk} x_{jit} x_{kit} + v_{it} - u_{it}, \tag{4.13}$$

where w_i is farm specific effect distributed normally with mean 0 and finite variance; u_{it} is the inefficiency effect varying over time distributed half normal with mean 0 and a constant variance; v_{it} is symmetric random error. Equation (4.13) can be estimated using maximum simulated likelihood due to three disturbances terms, w_i, v_{it}, and u_{it}. FRONTIER commands in LIMDEP were used for estimating the random effects model. Computational complexity of estimating a true fixed and random effects model precluded estimating the production function and finding significant factors equation simultaneously, although Greene (2012) stated it could be possible. Hence, a two-step regression approach was used to determine significant factors affecting efficiency.

For comparing the distribution of DEA and SFA, kernel density with logit function was used. A kernel density shows the distribution of a variable nonparametrically without any assumption of the underlying distribution. The horizontal axis in Figure IV-1 denotes bandwidth, which is analogous to the bin in a histogram and the vertical axis is a function of frequency observed at bandwidth h where

$$h = 0.9Q/n^{0.2} \text{ where } Q = \min(\text{std.dev.}, \text{range}/1.5) \tag{4.14}$$

where n is frequency, the interval of range was 100.

The technical efficiency scores determined by each of the DEA and SFA methods were used as dependent variables in regression models that included firm demographic and economic factors as independent variables. A two-step Tobit random effects model was used because many of the efficiency scores were bounded at one and the data are combined time series and cross section. The model was specified:

$$\begin{aligned} Y_{it} &= X_{it}\beta + u_i + e_{it} \quad \text{if } X_{it}\beta + u_i + e_{it} < 1 \\ &= 1 \qquad \text{otherwise,} \end{aligned} \tag{4.15}$$

where Y_{it} is a vector of technical efficiency scores at observation i and year t, X_{it} is matrix of demographic and economic variables at observation i year t, β is a vector of parameters, u_i is a vector of farm random effects distributed normally with mean 0 and variance σ_u^2, residual, e_i is a vector of error terms distributed normally with mean 0 and variance σ_e^2, u_i and residual, e_i are independent. The TOBIT command in LIMDEP version 10 (Greene 2012) was used to estimate equation (4.15).

Application to Surveyed Crop Farm Data

Data were collected from 141 crop farms in the Western Great Plains from Colorado, Kansas, Nebraska, Oklahoma, Texas, and Wyoming, during 2002-2005. For measuring efficiency scores, total gross revenue for all crops grown on the farm throughout the year was used as output, and expenditures for machinery, seed, fertilizer, chemicals, labor, land, and other costs associated with crop production were used as inputs. The units for inputs were monetary dollars. Machinery included fuel, repairs, custom machine hire; chemicals included herbicide, insecticide, and fungicide. Labor included the cost of hired labor and the opportunity cost of labor required for field operations. Land cost was calculated as the value of the county's average cash rent value times the farm's crop acres including fallow acres. Other costs included insurance, operating interest, overhead, depreciation, interest, and THI (taxes, housing, and interest). Output and inputs were chosen based on previous research. Most DEA researchers chose 6 to 7 input items for measuring efficiency of their resource allocation (Byrnes et al. 1987; Weersink et al. 1990, Kalaitzandonakes et al. 1992, Chavas and Aliber 1993; Featherstone et al. 1997; Wu et al. 2003).

There is no theoretical background for choosing the number of input items but according to Fernandez-Cornejo (1994) if the number of observations is n, and the number of inputs is m, and the number of outputs is k, then the dimensionality ratio $= \frac{n}{m+k}$. A dimensionality ratio which is less than four should be used for estimating an efficiency score.

Demographic and economic variables were used in the Tobit models. The demographic factors were age of operator, formal years of operator education, whether a farm uses internet (use of internet), and number of years the farm was operated by the same family (family operating years). Economic variables included proportion of crop revenue from government payments (Gov. payment), proportion of crop revenue from insurance payments (insurance payments), whether a farm obtained off-farm income (off-farm income), average number of cattle on the farm (number of cattle), whether a farm used insecticide (use of insecticide), and the number of power and implement machines used on the farm (number of power machines and number of implement machines), how much a farm relied on custom work (custom work rate), what proportion of the farm's cropped land was owned, cash leased, and share leased, the level of crop diversification (crop diversity), farm size (sales revenue), and tillage system (tillage).

The diversification, farm size and tillage variables were constructed as discrete variables. The farm size variable was based on a system used by Mugera and Langemeier (2011) in which farms with annual revenue greater than $500,000 were classified as large; medium farms were

$250,000 to $500,000, small farms were $100,000 to $250,000, and very small farms were less than $100,000 in annual revenue.

The classification of diversity was based on the ratio of the area of wheat and fallow to total land cropped. Farms in the upper 25% of the diversity ratio were classified as wheat-only. Farms in the lower 25% of the diversity ratio were classified as full diversity. Those farms in the middle 50% were classified as some diversity. A continuous variable of diversity was also tried for inclusion in the random effects model for comparison but they did not converge.

Three discrete tillage groups were formulated: no-till, minimum till, and conventional till. A farm was classified as no-till if the land was not tilled on the farm. A farm was classified as conventional till if the producer reported three or more tillage passes prior to seeding a crop. Farms that did not fit into the no-till or conventional till categories were designated as minimum till.

To remove random shock in the efficiency, year and state variables were included in the factors affecting efficiency equations. 564 observations for 141 farms were used to estimate efficiency scores because a farm had an observation for each of the four years. The descriptive statistics of data for inputs and output, variables for factors affecting efficiency are summarized in table IV-1 and IV-2.

Results

<u>Estimated Production Function Using SFA</u>

Stochastic frontier production functions were estimated by five different techniques of SFA, defined by equations (4.4), (4.7), (4.10), (4.12), and (4.13), as defined in the methods section. Findings are presented in table IV-3. Input items were chosen based on the items used for the DEA methods which conserved surveyed data structure. Translog functional forms were chosen based on the log likelihood test which tested Cobb-Douglas versus translog functional forms.

Although many parameters of SFA1 and SFA3 were not significant, the inefficiency effect parameter, gamma, was significant. The other significant parameters for inputs in SFA1 and SFA3, defined by equation (4.4) and (4.7) were similar, as expected, because both were based on the Battese and Coelli model (1992, 1995). The significant parameters were other inputs, square term of seed and machinery, and the interaction terms for land and seed, land and chemicals, and seed and labor. The time varying parameter, η, in SFA3 was not significant. This is not surprising since the data set included only four year observations.

The significant parameters for SFA2, defined by equation (4.10), were similar to those of SFA1 and SFA3, even though the magnitudes of significant factors were different. The parameters estimated by SFA4 and SFA5, defined by equations (4.12) and (4.13), are reported in columns 4 and 5 of Table IV-2. The number of significant parameters in SFA4 and SFA5 is greater relative to models SFA1, 2, and 3. The inefficiency effects, indicated by sigma *u* in these models were 0.35 and 0.28. The estimated results of inefficiency effects in this study were consistent with those of Greene (2005) who found an inefficiency effect of 0.43 in his true fixed effects and 0.32 in his random constant model with the health data.

To summarize, SFA1, SFA2, and SFA3 provided similar results. SFA4 and SFA5 also provided similar significant parameters. And, all of the SFA models indicated that inefficiency effects were significant in our study.

Measuring Technical Efficiency using DEA and SFA

The mean technical efficiency estimated by DEA, defined by equation (4.1), and SFA defined by equation (4.4), (4.7), (4.10), (4.12), and (4.13) are presented in table IV-4. The highest mean of technical efficiency scores was SFA5 with 0.87. The next highest was SFA4 with 0.81. The lowest mean technical efficiency scores of 0.46 were estimated by SFA2. Greene (2004a) argued that SFA2 could cause a downward bias. Cummins and Zi (1998) and Hjalmarsson et al. (1996) also found that SFA2 had the lowest technical efficiency score in their DEA and SFA models. Cummins and Zi (1998) argued that the lower technical efficiency scores produced by the SFA2 model could be a result of the large amount of random shock such as a failure of machine, bad weather, or incorrect constraint of the imposed time invariant constraint.

Mean technical efficiency scores of SFA1 (0.75) and SFA3 (0.76) were found to be similar. Figure IV-1 shows the technical efficiency distribution of the SFA scores. The kernel densities for SFA1, SFA2, and SFA3 have similar widely dispersed shapes. Whereas those of SFA4 and SFA5 have less dispersion with sharp peaks around 0.85. These shapes of SFA4 and SFA5 were similar to those reported by Greene (2005) who found that elimination of the time invariant effect resulted in a tighten distribution.

Figure IV-1 also shows the DEA technical efficiency distribution estimated by a kernel density. The distributions of technical efficiency among all DEA techniques are similar. They are spread relatively widely but have two peaks around the means and at one. Bauer et al. (1998) also found that DEA methods result in a relatively higher standard deviation compared to those of SFA methods. So the key difference is that SFA acknowledges noise in the data.

Rank-order Correlation of Technical Efficiency between DEA and SFA

Spearman rank-order and Kendall's Tau-b correlations of the DEA and SFA technical efficiency scores were estimated (table IV-5). The Spearman rank-order correlations within DEA ranged from 0.80 to 0.87 while those between DEA and SFA ranged from 0.30 to 0.63. The correlation between DEA and SFA in this study is lower than that reported by Cummins and Zi (1998) who found correlations ranging from 0.56 to 0.60. Murillo-Zamorano et al. (2001) reported correlations ranging from 0.83 to 0.89. However, Hjalmarsson (1996) reported correlations ranging from 0.23 to 0.75 which is more similar to the findings of the current study.

The technical efficiency scores estimated by SFA1, SFA2, and SFA3 were highly correlated ranging from 0.88 to 1.00. Similarly scores estimated by SFA4 and SFA5 were highly correlated at 0.92. However, SFA4 scores were not correlated with SFA1, SFA2, and SFA3. Scores estimated by SFA5 were weakly correlated with scores estimated by SFA1, SFA2 and SFA3 ranging from 0.22 to 0.24. These findings are consistent with those reported by Greene

(2005) who also found that correlation between the true fixed model and SFA2, which is the fixed effects model based on Cornwell et al. (1990) were only 0.052. Given the specific functional form used for the SFA models and given the data analyzed for this study, the technical efficiency scores within SFA models have more variation than between the SFA and the DEA models.

Figure IV-2 shows the correlation between DEAVP and SFA5. At lower scores, their correlation is lower because the dots in the figure were spread widely, while at higher scores, their correlation is higher because dots were spread narrowly.

The correspondence of the 25% best, defined as the farms on which its technical score ranked in the upper 25%, and 25% worst practice farms, defined as the farms on which its technical score were ranked lower 25%, as determined by DEA and SFA are presented in table IV-6 in time invariant efficiency and IV-7 with time variant efficiency. The top 25% of farms as measured by technical efficiency scores by one method such as DEAVP were compared to the top 25% as measured by an alternative method such as SFA3. The correspondence of random chance is 25%. The comparisons of DEA and SFA were separated from time invariant to time variant because they have different number of technical efficiency scores. SFA1, SFA2, DEAVA and DEAVC were grouped as time invariant because SFA1 and SFA2 had 141 technical efficiency scores over four years, and DEAVS and DEAVC compared 141 farms only because they had a single year' reference set. Whereas SFA3, SFA4, SFA5, DEAVP, and DEACP were grouped as time variant because their technical efficiency varied over time having 564 technical efficiency scores over four years. This means that the same farm in different year was treated as a different farm. It is possible that a farm included in the 25% best farms group in 2002 could be included in the 25% worst farm group in 2005.

The results reported in table IV-6 and IV-7 are similar to those reported in table IV-5. In time variant, within DEA methods are highly correlated, whereas within SFA there is considerable variability. It is noted that SFA3 and SFA4 in time variant group were not correlated, whereas SFA4 and SFA5 in time variant group were closely correlated.

Returns to Scale and Scale Efficiency

Input elasticities are measures of the percentage change in output resulting from a percentage change in input. The SFA estimated mean elasticities of inputs for the crop farms in the sample, as defined by equation (4.8) are reported in table IV-8. Miscellaneous inputs, which included insurance, operating interest, overhead, depreciation, interest, and THI had the highest elasticity of 0.36. The next highest input elasticity was for machinery. However, by this measure, fertilizer and chemicals and labor had little effect on the output of crop farms in the sample. Average of returns to scale of these farms was decreasing returns to scale based on the sum of elasticities of inputs which was less than one.

The DEA methods calculate scale efficiency differently than SFA methods. DEA scale efficiency implies if a score of scale efficiency is less than one, a farm has scale inefficiency. Scale efficiency (SE) for DEA can be calculated as:

$$SE = TECRS/TEVRS, \tag{4.16}$$

where TEVRS is score of technical efficiency under the model permitting variable returns to scale and TECRS is the score of technical efficiency under the model that assumes constant returns to scale. If the scale efficiency score for a farm is equal to one, then the farm is said to be scale efficient. This means that the farm is found to be operating at a point along its cost curve consistent with constant returns to scale. If the scale efficiency score is different from one then the farm is said to be scale inefficient. Scale inefficiency may result from a farm operating in either an increasing returns to scale region or a decreasing return to scale region.

To determine if the farm is operating in the increasing returns to scale or the decreasing returns to scale region, a second linear programming problem (non-increasing returns to scale) can be solved. The non-increasing returns to scale model is the same as equation (4.1) with one more constraint. The added constraint is an inequality (less than or equal to one) convex combination constraint. If the score of the non-increasing returns to scale model is the same as the score of technical efficiency under constant returns to scale, then the farm is found to be operating under increasing returns to scale. Otherwise, the farm is found to be operating in the decreasing returns to scale region.

Table IV-8 shows average of scale efficiency as estimated by DEAVP and DEAVS methods. The scale efficiency ranged between 0.87 and 0.91, indicating that scale inefficiency existed. By this measure, most of the farms included in the survey were operating in a region of decreasing returns to scale. Not many of the farms included in the sample operated under optimal scale, even though they were close to the optimal scale. The largest farm in the sample, located in Colorado, planted 24,527 acres in 2003 and the score of scale efficiency was 0.83. By this measure, the farm was operating under decreasing returns to scale.

In summary, although the calculation of scale efficiency was slightly different between DEA and SFA, the estimated results of returns to scale were similar, exhibiting on average decreasing returns to scale. Table IV-9 shows the Spearman rank-order correlation of scale efficiency between DEA and SFA. The correlation between SFA1 and SFA3 were high with a value of 0.95. DEAVP had higher correlation with SFA ranging from 0.32 to 0.37 compared to DEAVS, which had the correlation with SFA ranging from 0.13 to 0.15. Figure IV-3 shows the distribution of DEA and SFA scale efficiency which differ between two methods. DEA methods were widely skewed to the left, but most observations are close to one. The shape of distribution of scale efficiency scores estimated by SFA3 were tightly distributed with a peak near 0.90.

Demographic and Economic Factors Affecting Technical Efficiency

The two-step regression approach was used to determine significant factors affecting technical efficiency for all DEA methods and for SFA2, SFA4, and SFA5, defined by equation (4.2). Although the two-step approach could cause an omitted variable problem and violate the assumption of independent identical random errors, the two-step regression approach has been used in most studies. For the SFA3 method, a one-step approach was used. Equation (4.10) as estimated with maximum likelihood methods can be used to estimate the production function and reveal significant factors at the same time. Significant factors in SFA3 explained efficient effects negatively while other methods explained efficient effects positively

A comparison of SFA1 with other methods was omitted because SFA3 and SFA1 are the same due to the insignificance of the time effect. Table IV-10 and Table IV-11 shows significant factors affecting technical efficiency. Significant factors identified by DEAVP and DEAVS were similar. The significant factors were years of operator education, number of cattle, and farm size. In addition to these significant factors, proportion of cash leased land relative to total crop land and crop diversity were significant with DEAVP while DEAVS found that the proportion of crop share land relative to land cropped was significant.

The significant factors for the DEACP model were number of cattle, number of implement machines, and farm size, whereas only farm size was significant for the DEACS model. Similarly, the SFA1, SFA4 and SFA5 models also found that farm size was the only common significant factor. SFA2, a deterministic frontier function, had most of the significant parameters for independent variables. This appears that the inefficiency effect estimated by SFA2 in input variables used to estimate the production function and the demographic variables used in the Tobit model could be highly correlated. Most of the demographic and economic variables could be correlated time invariant factors because SFA4, which is also a fixed effects model but excluded time invariant factors, had only one significant factor, farm size. Tobit random effect models with fallow not included in diversity variable also were estimated in appendix for chapter IV .The results were similar.

In sum, the most common significant factor across all methods was farm size. By these measures, farm size affected significantly technical efficiency of the sample farms. The magnitude parameters of farm size explain that very small farms were the least technically efficient and small farms and medium farms were less technically efficient than large farms. Except for farm size, other factors found to significantly affect technical efficiency, differed across the estimated models.

Conclusions and Implications

The objective of this study was to compare DEA and SFA for measuring efficiency of crop farms in the Western Great Plains during 2002-2005. Data were obtained from 141 crop farms located in Colorado, Kansas, Nebraska, Oklahoma, Texas, and Wyoming. They were compared in terms of technical and scale efficiency with the Spearman rank-order and Kendall's tau-b correlations. Four different techniques of DEA and five different techniques of SFA were considered and used to compute efficiency. The results show that technical efficiency scores of DEA were lower than those of SFA, even though DEAVS, SFA1, and SFA4 were close to one another. The methods within DEA for measuring technical efficiency were highly correlated, whereas the methods within SFA varied considerably. Findings from SFA1, SFA2, and SFA3 were not correlated with findings from SFA4. However, the correlation between DEA and SFA4 and SFA5 were higher than those within SFA methods.

Both the DEA and SFA methods found that crop farms included in the sample were on the average operating under decreasing returns to scale. Spearman rank-order correlation of scale efficiency between DEA and SFA were lower than those of technical efficiency. This difference could be related to the different formula for measuring scale efficiency. SFA measures returns to scale as the sum of the elasticities of each input, whereas DEA measures the ratio of technical efficiency under constant returns scale to technical efficiency under variable returns to scale. To find factors affecting technical efficiency, the significant factors found within DEA techniques were similar. They were operator education and farm size as measured by annual gross revenue which were positively related to technical efficiency, whereas the only consistent significant factor found within SFA was farm size which were positively related to technical efficiency. Thus, all methods found that farm size did affect technical efficiency. The larger farms were more technically efficient than very small, small, and medium farms.

To summarize, the methods within DEA were not different for measuring technical efficiency, whereas within SFA methods were considerably different. In particular, SFA1, SFA2, and SFA3 were not correlated with SFA4 . Choosing a method between SFA and DEA or choosing within SFA could result in different efficiency scores and distributions.

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Table IV- 1. Summary statistics of data for calculating efficiency variables ($/producer/year).

Variables	Observations (no.)	Mean	Std. Dev.	Max	Min
Revenue	564	240,552	207,577	1,748,716	3,157
Machinery	564	36,811	34,748	435,248	1,401
Seeds	564	15,305	14,432	114,512	420
Fertilizer	468	33,396	39,243	263,601	1
Chemicals	496	21,484	40,965	457,825	1
Labor	560	6,165	4,962	43,439	1
Other	564	33,217	41,048	457,923	945
Land	564	62,501	55,634	438,843	2,920

Table IV- 2. Summary statistics of data for finding significant factors affecting efficiency

Variables	Definition	Mean	Std. Dev.
Age	Operator age (years)	49.4	10.67
Education	Operator formal education (years)	14.7	1.593
Internet use	Obtain producer-related information from the Internet; No=0, Yes=1	0.8	0.36
Family tenure	Years operation in farm family	72.03	33.0
Gov. payment	Prop. of gov. payments to total revenue	0.14	0.08
Insurance payment	Prop. of insurance payments to total revenue	0.12	0.19
Off-farm Income	No=0, yes=1	0.72	0.45
Livestock	Cattle (head)	329	688
Use of insecticide	No=0, Yes=1	0.8	0.36
Power machines	Number of power machines including tractors	4.7	2.36
Implement machines	Number of unpowered implements	11.5	5.1
Custom work	Custom work operations relative to total field operations	0.16	0.18
Cash rented land	% of farm land cash leased to total cropped land	0.16	0.23
Crop share rate	% of farm land crop share leased to total cropped land	0.42	0.33
Crop Diversity	Wheat-only =0, some diversity=1,full diversity =2	1	0.7
Farm Size	Very small=0, small=1, medium=2, large=3	1.2	0.9
Type of Tillage	No till=0, minimum till=1, conventional till=2	1.2	0.68
Number of Obs.	544		

Table IV-3. Stochastic frontier production model.

Variables	SFA1	SFA2	SFA3	SFA4	SFA5
Constant	2.37	-	2.39	-	2.65***
Land	-0.37	0.14	-0.35	-0.46	0.01
Machinery	-0.25	0.02	-0.30	-0.81**	-0.27
Seeds	0.42	0.06	0.39	0.72**	0.32
Fertilizer	-0.04	-0.10	-0.04	-0.06	-0.05
Chemicals	0.09	0.00	0.09	0.21***	0.06
Labor	0.09	-0.86	0.13	0.84***	-.24
Other	1.22**	1.84**	1.24**	0.54*	1.12***
Land2	-0.15	-0.14	-0.15	-0.19**	-0.20**
Machiner2	0.22*	0.12	0.23*	0.36***	0.19*
Seeds2	-0.18*	-0.15	-0.18*	-0.04	-0.16**
Fertilizer2	-0.00	-0.01*	0.00	0.018***	0.00
Chemical2	0.00	-0.00	0.00	0.01***	0.00
Labor2	-0.01	0.10	0.00	0.055***	-0.02
Other2	0.15	0.19	0.16	0.17*	0.18*
Land*Machinery	-0.05	-0.14	-0.05	-0.07	-0.07
Land*seed	0.27***	0.27***	0.27***	0.31***	0.31***
Land*fertilizer	0.02	0.02	0.02	0.02*	0.02*
Land*chemicals	-.03**	-0.018	-0.03**	-0.046***	-0.03***
Machinery*other	-0.15	-0.08	-0.16	-0.11	-0.13*
Seeds*labor	-0.09**	-0.12**	-0.09**	-0.09**	0.10*
Seeds*other	-0.10	-0.18	-0.11	-0.21***	-0.17***
Fertilizer*Labor	0.02**	0.026***	0.02**	0.014**	0.02**
Fertilizer*other	-0.03***	-0.02	-0.03***	-0.04	-0.03***
Chemicals*other	0.01	0.01	0.01	0.024***	0.02*
Lambda[a]	1.63	-	1.68	0.90***	0.91**
Gamma[b]	0.729***	-	0.714***	0.44[c]	0.46[c]
Sigma u	-	-	.352***	0.2858***	0.17
Sigma square[d]	0.18***	-	0.17***	.43***	0.26***
Log Likelihood value	-57.294	-	-57.135	-38.13	-50.91
Eta[e]	-	-	0.02	-	-
Number of obs.	564				

[a] Lambda is $\frac{\sigma_u}{\sigma_v}$, a parameter indicating inefficiency effect of SFA4 and SFA5 Lambdas for SFA1 and SFA3 were calculated manually based on the values of Gamma and sigma square obtained from FRONTIER software.

[b]Gamma is $\frac{\sigma_u^2}{\sigma_u^2+\sigma_v^2}=\frac{\sigma_u^2}{\sigma^2}$, a parameter indicating inefficiency effect of SFA1 and SFA3.

[c] Gammas in column 4 and column 5 were calculated manually based on sigma u, and sigma square obtained from LIMDEP software.

[d] Sigma square means $\sigma^2=\sigma_u^2+\sigma_v^2$

[e] Eta is time varying parameter for SFA3.

Notes: The dependent variable is total gross revenue for all crops per farm per year. SFA1 is a time invariant stochastic frontier model with random error term. SFA2 is a time invariant frontier model with deterministic inefficiency effect. SFA3 is a time variant stochastic frontier model which is similar to SFA1 but including a time variant parameter. SFA4 is a true fixed effect model which is similar to SFA2 but separates firm specific effects from the inefficiency effect , and includes a time variant inefficiency effect. SFA5 is a true random effects model which separates firm specific effects from the inefficiency effect.

Table IV-4. Mean technical efficiency for DEA and SFA (output oriented).

	Mean	Std. Dev.	Min	Max
DEAVP	0.69	0.21	.23	1
DEACP	0.60	0.22	0.15	1
DEAVS	0.80	0.20	0.27	1
DEACS	0.73	0.21	0.26	1
SFA1	0.75	0.13	0.42	0.96
SFA2	0.46	0.16	0.01	1.0
SFA3	0.76	0.13	0.42	0.96
SFA4	0.81	0.04	0.60	0.91
SFA5	0.87	0.04	0.64	0.96

Note: DEAVP is DEA using the entire 4 year data as a reference set under variable returns to scale. DEACP is DEA using the entire 4 year data as a reference set under constant returns to scale. DEAVS is DEA using a single year data as a reference set under variable returns to scale. DEACS is DEA using a single year data as a reference set under constant returns to scale.

Table IV-5. Spearman rank-order and Kendall's Tau-b correlation of technical efficiency between DEA and SFA.

	DEAVP	DEACP	DEAVS	DEACS	SFA1	SFA2	SFA3	SFA4	SFA5
DEAVP	1.00	0.87	.88	.80	.50	.33	.51	.52	.63
DEACP	0.72	1.00	.79	.89	.44	.19	.45	.48	.58
DEAVS	0.73	0.62	1.00	.87	.50	.30	.49	.41	.54
DEACS	0.63	0.72	0.75	1.00	.48	.24	.47	.42	.56
SFA1	0.36	0.31	0.37	0.34	1.00	.88	1.00	-0.01*	0.24
SFA2	0.24	0.14	0.22	0.17	0.71	1.00	.88	-0.01*	0.22
SFA3	0.36	0.32	0.36	0.34	0.97	0.71	1.00	-0.01*	0.24
SFA4	0.37	0.34	0.29	0.29	-0.01	-0.01	-0.00	1.00	0.92
SFA5	0.46	0.42	0.39	0.40	0.16	0.15	0.16	0.76	1.00

Notes: * denotes correlations are not statistically significant at 10 % level.

Spearman rank-order correlation is above diagonal; Kendall's Tau-b correlation is below diagonal.

Table IV-6. Correspondence of technical efficiency of DEA and SFA for 25% best and 25% worst[a] farms with time invariant efficiency.

	DEAVP	DEACP	SFA3	SFA4	SFA5
DEAVP	1.00	0.75	0.40	0.57	0.57
DEACP	0.72	1.00	0.40	0.48	0.48
SFA3	0.52	0.52	1.00	0.24	0.24
SFA4	0.47	0.42	0.23	1.00	1.00
SFA5	0.48	0.43	0.23	1.00	1.00

[a] 25 % best is defined as the farms of which technical efficiency scores ranked by upper 25percnet, whereas 25 percent worst is defined as the farms of which technical efficiency scores ranked by lower 25 percent given each samples.

[b] Time invariant method had 141 technical efficiency because technical efficiency are the same over four years. Thus, the numbers of each best and worst practice farms were 36.

[c] Time variant method had 564 technical efficiency. The technical efficiency score varied over the four years. The number of each best and worst practice farm was141.

Note: Each number in upper diagonal was the best practices correlation and each number in lower diagonal was the worst practices correlation.

Table IV-7. Correspondence of technical efficiency of DEA and SFA for 25% best and 25% worst[a] farms with time variant efficency[a].

	DEAVS	DEACS	SFA1	SFA2
DEAVS	1.00	0.83	0.5	0.47
DEACS	0.83	1.00	0.47	0.42
SFA1	0.58	0.56	1.00	0.78
SFA2	0.42	0.39	0.81	1.00

[a] Time variant method had 564 technical efficiency. The technical efficiency score varied over the four years. The number of each best and worst practice farm was141.

Note: Each number in upper diagonal was the best practices correlation and each number in lower diagonal was the worst practices correlation.

Table IV-8. Mean elasticity of inputs and return to scale (RTS) in SFA.

	Land	Machinery	Seed	Fertilizer	Chemicals	Labor	Other	RTS
SFA1	0.16	0.21	0.16	0.001205	0.012	0.036	0.358	0.9372
SFA3	0.16	0.19	0.17	0.000649	0.0124	0.0484	0.356	0.9375
DEAVP								0.87[a]
DEAVS								0.91[a]

[a] The value of RTS indicates the score of scale efficiency. It does not indicate returns of scale but does indicate scale inefficiency exists because the score is less than one. To determine returns to scale needs to solve non-increasing returns scales. The results shows that 112 observations were under increasing returns to scale, 411 observations were under decreasing returns to scale, and 41 observations were under constant returns to scale

Table IV-9. Spearman rank-order correlation [a] of scale efficiency between DEA and SFA

	DEAVP	DEAVS	SFA1	SFA3
DEAVP	1.00	0.32	0.37	0.38
DEAVS	0.32	1.00	0.13	0.15
SFA1	0.37	0.13	1.00	0.95
SFA3	0.38	0.15	0.95	1.00

[a]The number of above diagonal denotes Spearman rank-order correlation; the number below diagonal denotes Kendall's Tau-b correlation.

Table IV-10. Tobit random effect model for finding significant factor affecting technical efficiency for DEA and SFA using two-step approach.

Variables	DEAVP	DEAVS	DEACP	DEACS	SFA2	SFA4	SFA5
Constant	0.83***	.89***	.71***	.81***	0.38***	.84***	.90***
Age	.00	.001	.00	.00	-.001***	.00	.00
Education	.02*	.022*	.01	.01	.009***	-.00	.00
Use of internet	-.04	-0.069	-.02	-.03	.073***	-.00	.00
Family operating year	-0.001	-0.001	-.00	-.001	.002***	.00	-.00
Gov. payment	.16	.004	.19	.106	-.014	.05	.026
Insurance payment	.01	.087	.02	.050	.009	.02	.020
Off-farm income	.01	.024	.02	.02991	-.003	.000	.00
Number of head cattle	-.0001**	-.0001**	-.0004*	-.0005	.00	-.00	-.00
Use of insecticide	-.006	.005	-.024	.0059	.0345***	-.002	.003
N. of power machine	.00	.004	-.00	-.00157	-.013***	.0002	-.00049
N. of implement machine	.00	-.007	-.011**	-.00751	-.007***	-.00044	-.00038
Custom work rate	-0.07	.014	-.036	.059	-0.47***	.00	-.005
Lease rate	.13*	.129	.13	.102	-.09***	-.0033	-.003
Crop share rate	-.08	-.11*	-.05	-.076	-.042***	-.0027	-.006
Diversity							
Wheat only	.10*	.042	.089	.037	-.11***	.001	-.0006
Some diversity	.02	-.03	.01	-.037	-.13***	.001	-.002
Farm size							
Very small	-.42***	-.42***	-.245***	-.261***	-.05***	-.028***	-.035***
Small	-.37***	-.38***	-.2007***	-.208***	-.025***	-.025***	-.028**
Medium	-.23***	-.23***	-.1115**	-.111*	-0.12***	-.011	-0.12
Tillage							
No till	-.01	-.070	-.09	-.104	.070***	-.006	-.006
Minimum till	-.02	-.61	-.06	-.09	-.013***	-.003	-.007
2002	.00	.18***	-.011	.171***	.0065	-.011**	-.002
2003	-.05*	.122***	.04	.175***	.0094	.01*	.0154**
2004	-.01	.084***	-.023	.117***	.002	-.006	.00023
Colorado	-.04	-.05	-.056	-.071	.064***	-.002	.00086
Kansas	.12	.06	.102	.047	.155***	-.006	.0054
Nebraska	.08	.32	.089	.0586	-.065***	.002	.008
Oklahoma	.02	-.015	.010	-.02374	.138***	-.0086	-.00332
Texas	.09	.14**	.1215*	.1604**	.05599*	-.006	.0021
Log likelihood	36	-57	64	-26	938	1057	1,015
Number of obs.	544						

Table IV-11. Significant factors affecting technical inefficiency for SFA1 using one-step approach[a]

Variables	SFA3	
Constant	-2.27	***
Age	0.00	
Education	0.00	
Use of internet	0.01	
Family operating year	0.00	
Gov. payment	-0.09	
Insurance payment	-0.14	
Off-farm income	0.03	
Number of head cattle	0.00	
Use of insecticide	-0.07*	
N. of power machine	0.00	
N. of implement machine	0.00	
Custom work rate	0.01	
Cash lease rate	0.02	
Crop share rate	0.06	
Diversity		
Wheat only	-0.01	
Some diversity	0.01	
Farm size		
Very small	3.68	***
Small	3.25	**
Medium	2.84	***
Tillage		
No till	0.03	
Minimum till	0.08	
Year		
2002	0.03	
2003	-0.01	
2004	0.05	
State		
Colorado	-0.12	
Kansas	-0.26	***
Nebraska	-0.17	
Oklahoma	-0.16	*
Texas	-0.18	**
Gamma	0.437	**
Log likelihood value	114	

[a]one step approach means estimated production function and determining significant factors affecting efficiency was estimated at once rather than separately.

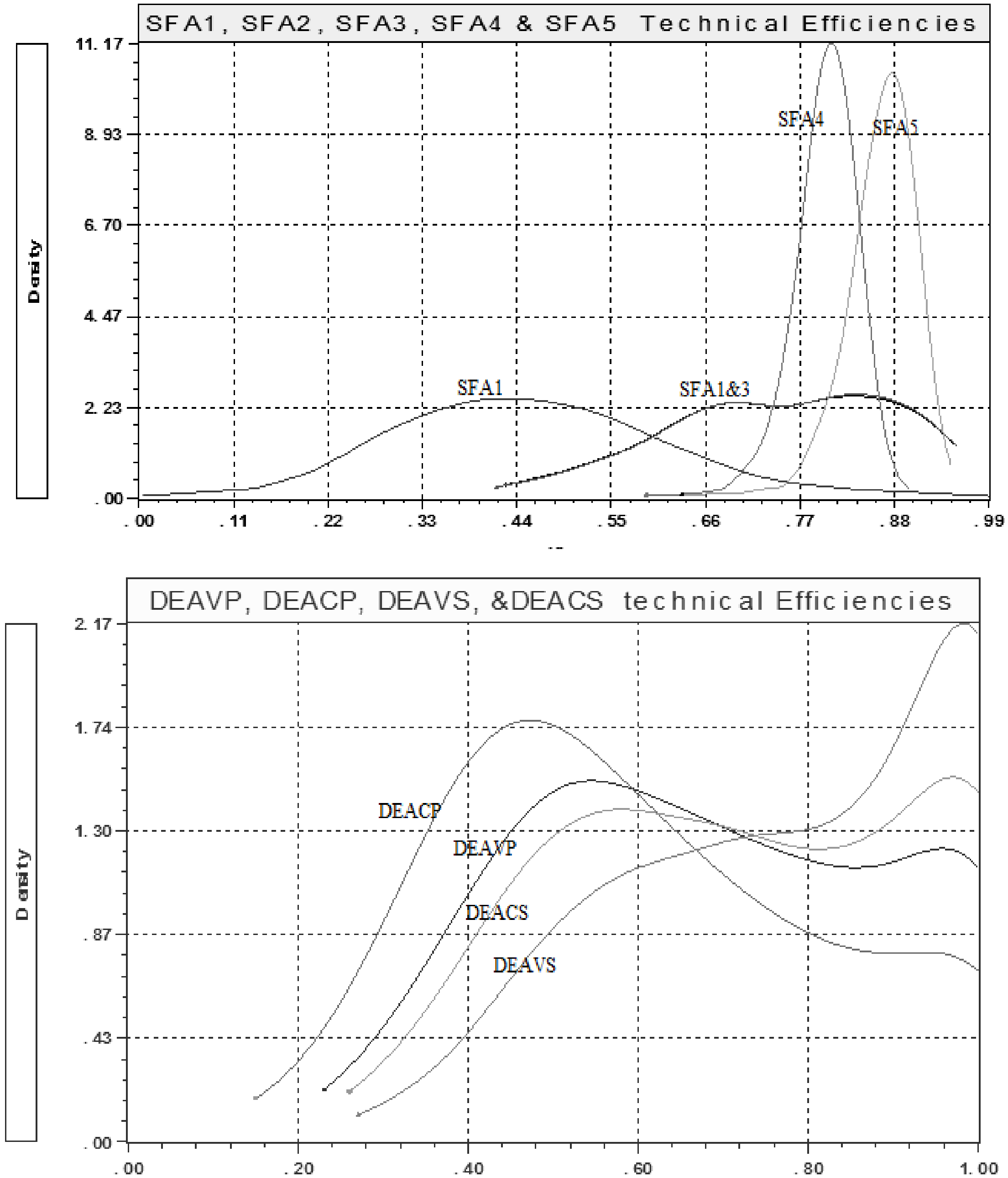

Figure IV-1. Kernel density of technical efficiency distribution among SFA and DEA methods**.**

Note: horizontal axis indicates bandwidth involved with number of observation and vertical axel indicates frequency of observed.

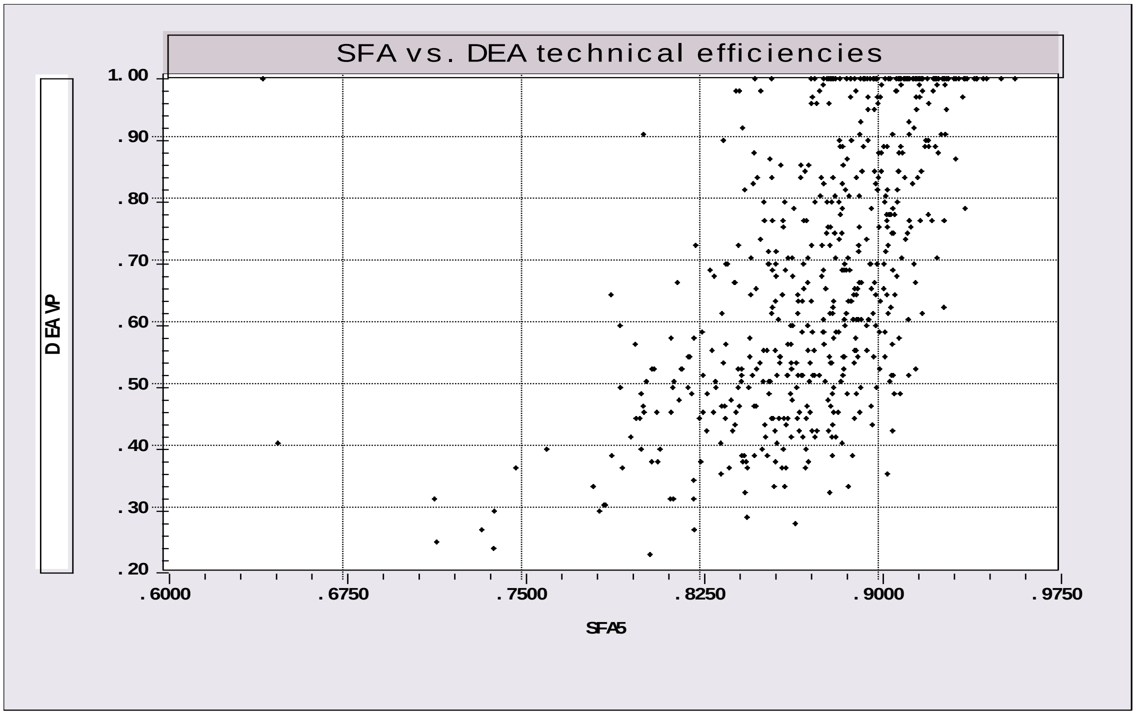

Figure IV-2. Correlation of technical efficiency between DEAVP and SFA5.

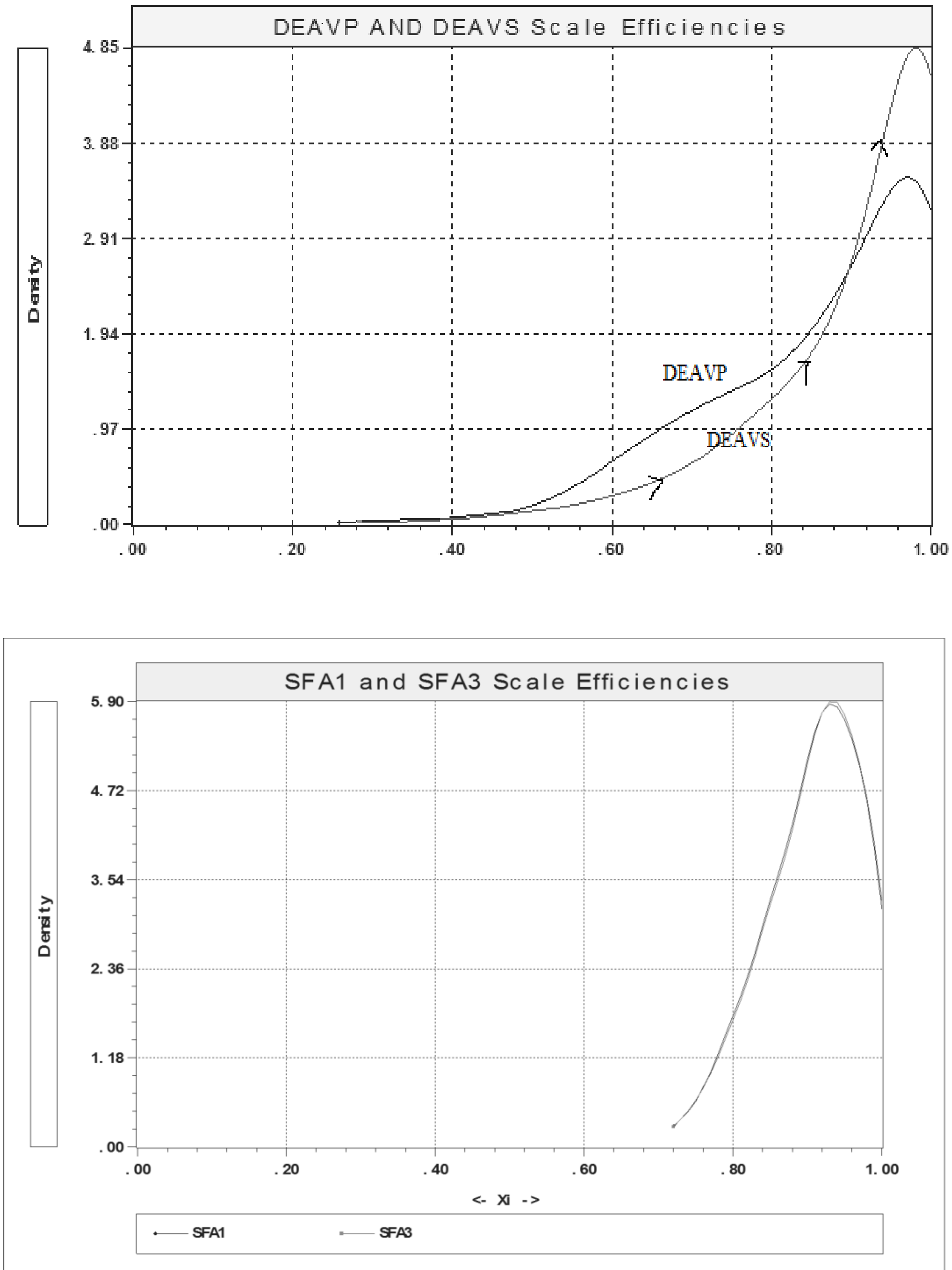

Figure IV-3. Kernel density of scale efficiency for DEA and SFA.

Appendix for Chapter IV

Table IV-12. Tobit random effect model for finding significant factor affecting technical efficiency for DEA and SFA using two-step approach with fallow not included in diversity variable.

Variables	DEAVP	DEAVS	DEACP	DEACS	SFA2	SFA4	SFA5
Constant	0.82***	.83***	.71***	.77***	0.38***	.84***	.90***
Age	.00	.001	.00	.00	-.004***	.00	.00
Education	.02*	.024*	.01	.01	.02***	-.00	.00
Use of internet	-.04	-0.075	-.03	-.04	0.001	-.00	.00
Family operating year	-0.001	-.001	-.00	-.000	.002***	.00	-.00
Gov. payment	.15	.003	.19	.108	-.01	.05	.028
Insurance payment	.01	.085	.02	.050	.009	.02	.020
Off-farm income	.002	.013	.01	.023	-.013***	.000	.001
Number of head cattle	-.0005**	-.0005**	-.0004*	-.0005	.0003***	-.00	-.00
Use of insecticide	-.012	-.002	-.031	.053	.045***	-.002	.003
N. of power machine	.0001	.003	-.001	-.0005	-.025***	.0002	-.00051
N. of implement machine	-.007	-.007	-.011**	-.008	-.007***	-.00044	-.00035
Custom work rate	-0.03	.009	-.046	.056	-0.13***	.004	-.005
Lease rate	.12*	.129	.12	.098	-.04***	-.0033	-.003
Crop share rate	-.100**	-.126**	-.07	-.085	-.015***	-.003	-.006
Diversity							
Wheat only	.11**	.08	.092*	.053	-.07***	.002	-.0009
Some diversity	.040	.025	.033	0.001	-.03***	.002	-.002
Farm size							
Very small	-.42***	-.42***	-.247***	-.264***	-.015***	-.028***	-.035***
Small	-.37***	-.38***	-.201***	-.210***	.001	-.025***	-.028**
Medium	-.23***	-.23***	-.110**	-.112*	-0.006	-.011	-0.12
Tillage							
No till	-.01	-.054	-.09	-.10	.003	-.006	-.006
Minimum till	-.02	-.53	-.06	-.09*	-.015***	-.003	-.007
2002	.00	.18***	-.011	.171***	-.008	-.011**	-.002
2003	-.05*	.122***	.04	.175***	-.006	.01*	.0154**
2004	-.01	.084***	-.023	.118***	-.002	-.006	.00014
Colorado	-.04	-.05	-.059	-.073	.127***	-.002	.00086
Kansas	.13	.09	.109	.064	.312***	-.006	.006
Nebraska	.08	.042	.086	.0586	0.80***	.002	.008
Oklahoma	.006	-.016	.003	-.030	.254***	-.0085	-.0036
Texas	.09	.14**	.114*	.151**	.177***	-.006	.0018
Log likelihood	36	-57	63	-27	964	1057	1,015
Number of obs.	544						

Table IV-13. Significant factors affecting technical inefficiency for SFA1 using one-step approach with fallow not included in diversity variable.

Variables	SFA3	
Constant	-2.14	***
Age	0.0006	
Education	-0.0045	
Use of internet	0.008	
Family operating year	0.0001	
Gov. payment	-0.09	
Insurance payment	-0.14	
Off-farm income	0.03	
Number of head cattle	0.00	
Use of insecticide	-0.07*	
N. of power machine	-0.004	
N. of implement machine	0.0024	
Custom work rate	0.01	
Cash lease rate	0.02	
Crop share rate	0.06	
Diversity		
Wheat only	0.01	
Some diversity	0.02	
Farm size		
Very small	3.53	***
Small	3.11	**
Medium	2.70	***
Tillage		
No till	0.04	
Minimum till	0.08	*
Year		
2002	0.03	
2003	-0.01	
2004	0.05	
State		
Colorado	-0.11	
Kansas	-0.26	***
Nebraska	-0.16	**
Oklahoma	-0.17	*
Texas	-0.16	**
Gamma	0.437	**
Log likelihood value	117	

VITA

Pilja Park Vitale

Candidate for the Degree of

Doctor of Philosophy

Thesis: MANAGEMENT PRACTICES AND EFFICIENCY OF WINTER WHEAT PRODUCTION IN WESTERN GREAT PLAINS

Major Field: Agricultural Economics

Biographical:

Education:

Completed the requirements for the Doctor of Philosophy in agricultural economics at Oklahoma State University, Stillwater, Oklahoma in July, 2013.

Completed the requirements for the Master of Science in agricultural economics at Texas A&M University, Collage Station, Texas in 2002.

Completed the requirements for the Bachelor of Science in agricultural economics at Seoul National University, Seoul, South Korea in 1989.

Experience:

2006-Present	Vegetable farmer, Promised Prairie Farm, Glencoe, Oklahoma
1989-2005	Cost analyst, Farm Management Bureau, Rural Development Administration, Suwon, South Korea