Effect of crop insurance on farm productivity of Kansas farms, US

Weldensie Embaye
Kansas State University, Department of Agricultural Economics
332D Waters hall, Manhattan, KS 66502
E-mail:wembaye@ksu.edu

Jason Bergtold
Kansas State University, Department of Agricultural Economics
307 Waters hall, Manhattan, KS 66502
E-mail:bergtold@ksu.edu

Ben Schwab
Kansas State University, Department of Agricultural Economics
310 Waters hall, Manhattan, KS 66502
E-mail: benschwab@ksu.edu

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Abstract

We evaluate the impact of crop insurance on Malmquist index, which is a combination of catch-up and frontier shift in Kansas. We employ a DEA Bootstrapped Malmquist index to measure the impact of crop insurance on the measured efficiency of farmers in the Kansas Farm Management panel survey from 1993-2015. Generally, crop insurance is endogenous variable to a model. We tested whether or not crop insurance is endogenous to the model using Durbin and Wu-Hausman tests. Both tests are highly statistically significant implies that crop insurance is endogenous to the model. To address endogeneity issue, we used Two Stage Least Square (2SLS) method. We exploited crop insurance subsidy regime change in 2001, which is external to the model, an important methodological identification as an instrument to crop insurance. Our results indicate that crop insurance affects catch-up and frontier shift positively and negatively respectively. However, the effect of crop insurance on Malmquist index is statistically insignificant. It increases catch-up on average by 32 percent and decreases frontier shift by about 29 percent. Overall, these positive and negative effects cancel out leads to no effect of crop insurance on Malmquist index. We conclude that crop insurance is not socially optimally used by Kansas farmers.

Keywords: Crop Insurance Subsidy, Bootstrapped DEA, Malmquist index, Kansas

Introduction

Provision of crop insurance over the last two decades has expanded significantly in the US. The government, through the USDA Risk Management Agency, provides large premium subsidies to farmers. Recently, crop insurance subsidies have reached $10 billion per year (Goodwin and Smith, 2013). Due to the Agricultural Risk Protection (ARP) of 2000-year policy, insurance subsidies the insurance cost paid by the government, after 2001 reached over 50 percent. For example, in Kansas the years 2000 to 2001, crop insurance subsidies jumped from 35 percent to 58 percent (figure 1). The primary objective of crop insurance is to increase agricultural production and stabilize farm income (Srorri et al., 2012; Young, Vandeveer, and Schnepf, 2001). It is evident that subsidies can attract more farmers to crop insurance participation. Makki and Somwaru (2001) stated that after an increase in crop insurance subsidies, the number of insured farmers increased significantly.

Linking crop insurance to technical efficiency and innovation is important. Due to limited availability of land and other natural resources, as well as an increasing population, increasing agricultural production through increases in technical efficiency and innovation is crucial to alleviate future food security issues. By associating crop insurance subsidies to efficiency and innovation, farmers may produce at higher levels of technical efficiency and innovation. Increases in technical efficiency and innovation, can be achieved through increases in output using the same level of input use and/or decreases in input use with the same level of output production (Farrell, 1957).

Even though, the primary objective of crop insurance is not for technological and/or technical improvement, there is a strong need to associate the use of crop insurance to these important features of farm production. Positive effects of crop insurance on technical efficiency and/or innovation are more likely to yield overall improvements to social welfare. Crop insurance subsidies are a major issue in the current and future Farm Bills. Being able to link crop insurance to technological and technical progress, can help risk averse farmers reduce the amount of input use per output, helping them to improve the economic viability of the farm and potential impacts on the environment. For example, farmers can use the monies saved from crop insurance income to invest into more efficient technology or crop varieties that would not have been bought due to capital constraints. Moreover, cost advantages due to improvement in farm productivity associated to crop insurance subsidies may give farmers to increase their ability to supply their output at lower prices, increasing their competitiveness. This may further motivate farmers to participate in crop insurance programs with subsidies if they utilize the savings for this purpose.

Crop insurance subsidies are labeled as a trade distortive measure, which is heavily criticized by the World Trade Organization (WTO). Linking it to technical efficiency and innovation would help to better negotiate WTO legal challenges to U.S. Farm Bill Programs (Steinberg and Josling, 2003; Young and Westcott, 2000). Given all these reasons, it is advantageous to study the effect of crop insurance on innovation and technical efficiency and the resulting policy implications. To our knowledge, studies on the effect of crop insurance on innovation and technical efficiency especially after 2001, where there was a significant increase in crop insurance subsidies has been limited in the US.

The theoretical relationship between crop insurance and technical efficiency is ambiguous. Though provisions of more crop insurance might better aid farmers to overcome financial constraints and invest in highly efficient technologies, it may also produce income guarantees to farmers, resulting in a reduction of efforts to innovate and/or produce efficiently (Smith and Goodwin, 1996). The primary objective of crop insurance is not to promote technical efficiency and therefore it might also have no effect.

Srorri et al. (2012) examined the impact of crop insurance on farm performance and indicated that crop insurance affected farm performance negatively. Note that substantial increases in crop insurance subsidies has a considerable effect for a farmer's crop insurance participation (O'Donoghue, 2014; Makki and Somwaru, 2001). O'Donoghue, (2014), indicated that increase in subsidies leads to large increase in crop insurance coverage levels. Literature indicates that subsidies have an ambiguous impact on technical efficiency. Minviel and Latruffe (2017) provided a meta-analysis on the effect of various type of subsidies on technical efficiency and found that generally subsidy have negative effects on technical efficiency. Forty-six percent of the papers reviewed by Minviel and Latruffe, (2017) showed no effect or a negative effect of subsidies on technical efficiency.

Latruffe et al. (2017) examined the effect of farm subsidies on technical efficiency of agricultural producers in Europe for the years 1990 to 2007. This study used stochastic frontier analysis and method of moment models to examine the policy impact and identified that the effect of subsidies was positive in Spain and Portugal, negative in Belgium and United Kingdom and had no effect in Denmark, Germany, France and Ireland. Similarly, Zhu et al. (2012) studied the effect of the Common Agricultural Policy (CAP) subsidies in Germany, Sweden and Netherlands over the years 1995-2004. Zhu et al. (2012) employed a translog stochastic frontier model and reported that subsidies showed a negative association with technical efficiency across the three European countries. Sckokai and Moro (2009) assessed the impact of the Common Agricultural Policy (CAP) single payment on output and investment using a normalized quadratic function in Italy and indicated that the policy had a significant effect on investment, but not on output. Moreover, Hadley (2006), using classical stochastic frontier model for the years 1982 to 2002, found a significant and positive impact of subsidies on technical efficiency for beef farms in Wales and England. Serra et al. (2008) examined the impact of decoupled payments on technical efficiency using a stochastic frontier model of agricultural producers in Kansas. Using data from 1998 to 2001, government programs such as decoupled payments decreased technical efficiency.

The purpose of this study is to evaluate the impact of crop insurance on farm productivity (technical efficiency and innovation) in Kansas. We employ Data Envelopment Analysis (DEA) technique to assess the direct and indirect impact on different efficiency measures. The effect of subsidy on farm innovation and technical efficiency can be measured in three ways. (i) First, the effect of a crop insurance on technical efficiency, measured using a 'catch-up' effect. (ii) Second, as the impact on an innovation in technology that indirectly results from the crop insurance as captured by a frontier-shift effect. (ii) Third, an overall farm productivity index (i.e. product of catch-up and frontier-shift effect) using the Malmquist index.

Our results indicate that the effect of crop insurance on catch-up, and frontier shift is statistically significant at 5% levels. Crop insurance increases catch-up effect by about 32 percent but decreases frontier shifts by about 27 percent. However, crop insurance shows no effect on Malmquist index. This implies that the opposite effect of crop insurance on catch-up and frontier shift cancels out to each other, and leads to no effect on overall productivity. We conclude that crop insurance is not socially optimally used by Kansas farmers.

Our paper contributes to the literature on farm production and policy evaluation in three ways. First, we consider effect the crop insurance on technical efficiency, innovation and Malmquist index, where previous study is limited. Second, we focus on the effect of the crop insurance in US—while most other limited studies focus on European countries. Lastly, we examine the effect of crop insurance by instrumenting using crop insurance subsidy regime change in 2001, which is external to the model, an important methodological identification as generally, buying crop insurance is endogenous to production (Srorri et al., 2012).

Theory

Modeling the impact of a crop insurance subsidy technical efficiency

We assume that farmers maximize profit. Improvement in technical efficiency helps farmers to obtain maximum output for a given input or producing an output level using minimum input required (Farrell, 1957). Following Battese and Coelli (1988), we define efficiency as average productivity (APP).

$$\mathrm{E(S)} = \frac{Y(X(S))}{X(S)}, \quad (1)$$

where E(S) represents technical efficiency. Here we model efficiency as function of crop insurance (S), through its effect on the allocation of the X-input, and ultimately of the Y-output.

The optimal effect of crop insurance on technical efficiency can be derived from the first order derivative of efficiency with respect to S, which is equal to:

$$\frac{\partial E}{\partial S} = \frac{\frac{\partial Y(X)}{\partial S}X - \frac{\partial X}{\partial S}Y}{X^2} \quad (2)$$

Assuming input and output prices are constant, we will see a crop insurance effect if $\frac{\partial Y(X)}{\partial S} \neq 0$ and/or $\frac{\partial X}{\partial S} \neq 0$. This implies, crop insurance may result in higher output using the same level of input and/or same level of output at lower level of input. Using insurance income acquired by through payment of crop insurance subsidy and insurance premium, farmers could purchase efficient technology, fund labor training, and research and development programs that overall improve farm productivity, or insurance income could motivate farmers to reduce investment effort as it is considered as source of income or it may not change farmers' production behavior. Hence, there is no conclusive theory regarding the effect of crop insurance on technical efficiency. It is truly an empirical question.

Data and Empirical strategy

Data

Data is from Kansas Farm Management Association that surveys Kansas farm information each year. Our data includes survey date collected from 1993-2015. Table 1 presents the summary statistics of key variables over the range of the specified years. The average age of the operator is around 56 years old. The data include: a single output, value of farm production, and six inputs, machinery, fertilizer, seed, pesticide, labor and irrigation. The average annual value of farm production is $390,265. The largest annual average cost of farms is machinery. It is about $57, 230 per year. Similarly, fertilizer alone costs farmers on average $43,715 per year. Following fertilizer, seed and pesticide ranked 3rd and 4th highest costs for farmers. The average annual cost for seed and pesticide are $26,738 and $22,304 per year respectively. Labor and irrigation that have an annual average cost of $19,711 and $1,588 per year. Crop insurance is important to protect against farm risks (production and price risks). Kansas farmers similar to other US farmers have highly subsidized crop insurance. The average annual insurance premium per farmer is $759. Since, 2001, crop insurance subsidy has increased significantly (see figure 1). Similarly, in exchange to government regulation and requirements, farmers get paid by the government. The average annual government payment per farmer is about $25318.

First Stage of Malmquist Data Envelopment Analysis (MDEA)

SFA and DEA are the two common methods used to measure Farm productivity. The methods are data envelopment analysis, non-parametric method that does not assume any functional form and stochastic frontier analysis that assumes functional form and incorporates random noisy. DEA is preferred over SFA when the sample is small or to medium size (Banker et al. 1993; Gong and Sickles, 1992). Since, we have only 158 farms, we have chosen DEA over SFA. Because of data restriction (single output and multiple inputs), input oriented over output oriented approach is chosen.

Farm productivity is measured using Malmquist productivity index. Malmquist index perform tremendous amount of job on measuring growth rate per unit of inputs (technical efficiency) and innovation (technological change). Unlike other type of real growth measure such as real GDP per capita, Malmquist index require less assumption and no price information (Kruger, 2003). Malmquist index can be broken down in to change in technical efficiency (CI) and change in technology (FS) (Fare et al., 1997).

The formulas for each index is as follows:

$$MI = \frac{d^t(Y_t,X_t)}{d^s(Y_s,X_s)}\left[\frac{d^s(Y_t,X_t)}{d^s(Y_s,X_s)}\frac{d^t(Y_t,X_t)}{d^t(Y_s,X_s)}\right]^{0.5} \quad (3)$$

$$CI = \frac{d^t(Y_t,X_t)}{d^s(Y_s,X_s)} \quad (4)$$

$$FS = \left[\frac{d^s(Y_t,X_t)}{d^s(Y_s,X_s)}\frac{d^t(Y_t,X_t)}{d^t(Y_s,X_s)}\right]^{0.5} \quad (5)$$

Where MI-Malmquist Index, CI-Catch-up effect, FS-Frontier Shift.

Each parameter such as MI, CI, and FS measures the index change between two periods, period s and t. It's is a distance function that measures the point $d^t(Y_t, X_t)$ relative to the point $d^s(Y_s, X_s)$. d^t and d^s are the technology references for the time s at period one and time t at period 2.

Traditional DEA is heavily criticized for not accounting for the effect of environmental variables on the production function or technology. Traditional DEA assumes that environmental variables explain only the difference within firms. However, Simar and Wilson (2007) stated that environmental variables still have potential to affect the frontier used to measure efficiency scores. Simar and Wilson, (2007) underscore the importance of accounting effect of environmental variables on the first stage of DEA for valid inferences in the second stage. To correct the biasness in the first stage, we calculated the DEA Malmquist index through bootstrapping the first stage that gives similar results to calculating DEA conditioning on environmental variables (Simar and Wilson, 1998). Bootstrapped DEA Malmquist index is similarly employed by other studies such as Wang and Lan (2013), Wang and Lan (2011), and Odeck (2009).

Technical efficiency for Malmquist index is measures using linear programing (see Wang and Lan, 2011; Coelli and Perelman, 1996) as follows:

$d^w(Y_z, X_z) = minmizing\ \theta$, subject to $\sum \lambda_j X_{kj} < \theta X_{s0},\ \sum \lambda_j Y_{rj} > Y_{r0}\,, \lambda_{ij} \geq 0$,

Where w = s, t, z = s,t, k = 1, 2, …, m, are weights assigned to each input, r = 1, 2, …, q, are weights assigned to each output.

Ordinary Least Square (OLS) Model

The effect of crop insurance on catch-up, frontier shift and Malmquist index, second stage DEA is estimated using OLS model. We use crop insurance as variables of interest. Crop insurance is equal to 1 if farmer buy insurance and 0 otherwise. This is difference in difference where crop insurance is equal to 1 and 0 in each year represents treatment and control group respectively. Buying crop insurance is farmer specific decision that depends on many factors, which is endogenous to the system. To overcome this endogeneity problem, an instrumental variable method is used. We use crop insurance subsidy policy change in the year 2001, which is external to the model as an instrument. We exploited the crop insurance subsidy police change (Agricultural Risk Protection ACT of 2000) in the year 2001. Crop insurance subsidy was provided to farmers through all the years of the study. However, it dramatically increased since the year 2001. Our instrument variable, crop insurance subsidy is a dummy variable which is equal to 1 if year is equal to or greater than 2001 and 0 otherwise. The IV estimation is implemented using Two Steps Least Square method (2SLS). The first step involves fitting a binary response model (probit) for crop insurance ($\hat{S}$) on the instrument. The second stage follows by regressing farm productivity measures on $\hat{S}$ and other control variables (D).

Two Steps Least Square method (2SLS):

$$S_{it} = \alpha IS_{it} + \beta D_{it} + e_{it} \quad \text{……………………………………………………………………………….. (6)}$$

$$Z_{it} = \delta \hat{S}_{it} + \varphi D_{it} + \varepsilon_{it} \quad \text{……………………………………………………………………….. (7)}$$

Where Z_{it}- farm productivity index such as MI, CI and FS for farmer I at time t, S-crop insurance, IS-insurance subsidy, D-control variables, α , β, δ and φ are parameters, and ε_i- is a mean 0 IID error term.

Result and Discussion

Table 2 presents Bootstrapped DEA farm productivity results. These farm productivity measure are an average values over the years 1993-2015. Efficiency scores are obtained using FEAR R package (Wilson, 2008). The average catch-up effect by region is 1.069 in region 1, 1.117 in region 2, 1.144 in region 3, 1.065 in region 4, 1.106 in region 5, and 1.074 in region 6. Overall, the average catch-up effect is 1.080. This implies that overall there is an average technical efficiency gain of 8 percent over the years 1993-2015. A frontier shift measures the overall technological progress. Frontier shift results are presented in the second column of Table 2. The average frontier shifts for region 1, 2, 3, 4, 5, and 6 range from a low of 1.086 (region 4) to a high of 1.411 (region 3), 1.290, and 1.235 respectively. Overall, the average frontier shift is 1.169 over the study years, suggesting an increase of 16.9 percent.

The average Malmquist index, the product of catch-up and frontier shifts, by region is 1.309 in region 1, 1.421 in region 2, 2.121 in region 3, 1.251 in region 4, 1.922 in region 4, and 1.589 in region 6. Overall, we estimate the average Malmquist index at 1.464 over the time span of the study. This means that over the specified years in this study, farm productivity has increased by 46.4 percent. The reasons for this farm productivity effect are combination of technical and technological progress. Kansas farms experience higher productivity growth as compared to china farms. Mao and Koo (1997), studied farm productivity growth of farms in various province of china and indicate that china farms showed 2 to 5 percent farm productivity growth. It could be the reason that Kansas farmers equipped with more advance technology may have higher skills than china farmers. However, this study covers recent and more years than the study by Mao and Koo (1997).

The effect of crop insurance on farm productivity indexes is examined in the second stage. Because adoption of insurance is endogenous to production, we instrument it using the change in crop insurance subsidy policy change from the enactment of the Agricultural Risk Protection Act (ARPC) in 2000, which is exogenous to the model. We assume that crop insurance subsidy affects farm productivity only through crop insurance. We tested whether or not crop insurance is endogenous to the model using Durbin and Wu-Hausman tests. Durbin and Wu-Hausman tests are 14.887 and 14.938 with P-value of 0.0001 implies that crop insurance is endogenous to the model. As a result, follow stage of least square regression. In the first stage, we instrumented crop insurance. Table 3 presents the effect of instrumental variable on crop insurance. Results shows that the effect of crop insurance subsidy policy change on crop insurance is highly significant that indicate that there is strong association between the instrument variable and crop insurance. In the second stage, we regress prediction value of crop insurance on farm productivity indexes. Table 4, presents the effect of crop insurance on farm productivity measures. Our results include regional fixed effect and without regional fixed effect. Results with and without regional fixed effect are quite similar. This implies that our methods are robust. The impact of crop insurance on catch-up effect is positive and statically significant at 5 % levels. Farmers who buy insurance have 32 percent higher catch-up effect than farmers who don't buy crop insurance. However, the impact of crop insurance on frontier shift is negative and statistically significant at 5 % levels. It means that farmers who buy insurance have 27 percent less frontier shift as compared to farmers who don't buy crop insurance. Overall, the crop insurance shows no effect on farm productivity or Malmquist index. This could be associated to the opposite sign of impact crop insurance on catch-up and frontier shift. We know that Malmquist index is a combination of catch-up and frontier shift. Hence, opposite sign of effect of crop insurance on catch-up and frontier shift leads to no effect of crop insurance on Malmquist index.

Our results confirm, that crop insurance have mixed effect on farm productivity. Crop insurance is highly subsidized in US. Farmers should keep putting enough effort despite the amount of crop insurance subsidy they get. It's great that crop insurance leads to higher technical efficiency. However, it is not acceptable that crop insurance leads to lower innovation or new technology adoption. This means that farmers are not investing enough in research and development or buying new technologies that leads to higher frontier shift. Their competitive advantage driven by higher technical efficiency is lost due to decline in innovation or lack of new technology adoption. This hinder or slows down farmers from become competitive in the market. Competitive farmers could benefit not only to themselves but to consumers as well. More competitive farmers could deliver more food supply at lower prices that benefits to consumers, which may lead to certain degree of increase in social welfare or standard living of the society. In other ways, positive association between crop insurance and catch-up, frontier shift and Malmquist index, benefit producers, consumers and it could contribute on convincing the government to continue to fund (subsidize) the program.

Conclusion

Provision of crop insurance over the last two decades has expanded significantly in the US. Crop insurance plays a remarkable role in increasing agricultural production and stabilizing farmer's income. Crop insurance subsidy are behind the main reason for farmer's participation in crop insurance. Crop insurance that increases farm productivity has much greater benefit to the society than otherwise. This implies that it's imperative to link the effect of crop insurance on innovation and technical efficiency. To our knowledge, studies on the effect of crop insurance on innovation and technical efficiency especially after 2001, where there was a significant increase in crop insurance subsidies has been limited in US.

We study the effect the of crop insurance on catch-up efficiency, frontier shift and Malmquist index using 1993-2015 farm level data in KS. We employ bootstrapped DEA model to examine the crop insurance impact on farm productivity. Generally, crop insurance is endogenous variable in a model. We tested whether or not crop insurance is endogenous to the model using Durbin and Wu-Hausman tests. Durbin and Wu-Hausman tests are statistically highly significant implies that crop insurance is endogenous to the model. To address endogeneity issue, we used 2SLS method. We exploited crop insurance subsidy regime change in 2001, which is external to the model as an instrument to crop insurance. Our results indicate that crop insurance affects catch-up and frontier shift positively and negatively respectively. However, the effect of crop insurance on Malmquist index is statistically insignificant. It increases catch-up on average by 32 percent and decreases frontier shift by about 29 percent. Overall, these positive and negative effects cancel out leads to no effect of crop insurance on Malmquist index. We infer that crop insurance is not socially optimally used by Kansas farmers.

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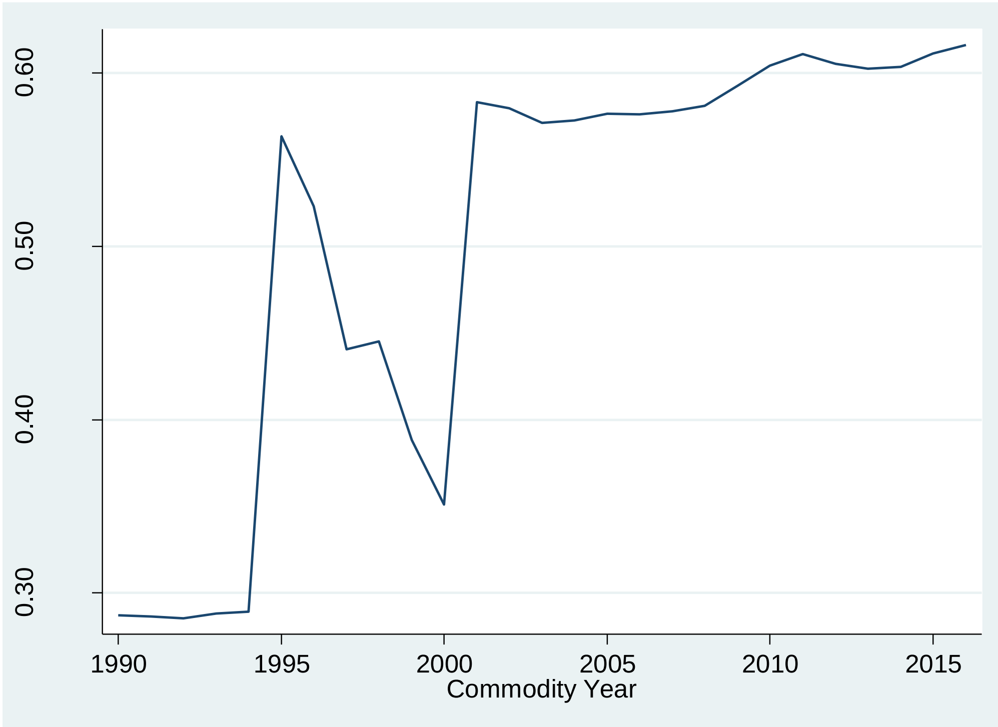
Figure 1: Average subsidy coverage by year in Kansas



Source: USDA Risk Management Agency

Table 1: Summary statistics of sample households' characteristics (panel data 1993-2015)

Variable	Definitions	Mean	Stand error
Value of farm production	Average annual value per farmer in dollar	390265.60	401230
Labor price	Labor price per acre in dollar	25.07	4.56
Other inputs price	Other inputs price per acre in dollar	33.53	16.29
Machinery price	Machinery price per acre in dollar	104.00	55.16
Crop price	Crop price per bushel in dollar	4.83	1.90
Labor cost	Average labor cost per farmer in dollar	19711.80	37153.52
Machinery cost	Average annual cost per farmer in dollar	57230.17	57212.61
Irrigation cost	Average annual cost per farmer in dollar	1588.1	6422.364
Land	Average crop land area per farmer in acre	1266.21	949.29
Pesticide	Average annual cost per farmer in dollar	22303.47	28570.06
Seed	Average annual cost per farmer in dollar	26737.68	39448.91
Fertilizer	Average annual cost per farmer in dollar	43714.97	65128.24
Insurance premium	Average annual cost per farmer in dollar	7591.20	11477.34
Operator age	Average age of an operator	56.40	10.69
Crop insurance subsidy	1 if year after 2001 and 0 otherwise	0.65	0.47
Government payment	Average annual government payment per farmer in dollars	25318.71	28131.66
Number of farmers			
	Region 1	33	
	Region 2	21	
	Region 3	7	
	Region 4	33	
	Region 5	2	
	Region 6	62	
Total number of farms		158	

Table 2: Farm Productivity for Kansas farmers: Bootstrapped DEA

Region	Catch up	Frontier shift	Malmquist index
1	1.069	1.093	1.309
2	1.117	1.137	1.421
3	1.144	1.411	2.121
4	1.065	1.086	1.251
5	1.106	1.290	1.922
6	1.074	1.235	1.589
All	1.080	1.169	1.464

Table 3: Modeling effect of insurance subsidy on demand for crop insurance using Probit

Variable	Coefficient	Standard error
Constant	-0.585	0.383
Insurance subsidy	0.751***	0.076
Ln non-farm income	-0.070***	0.017
Family size	-0.005	0.030
Age of operator	-0.016***	0.005
Ln government payment	0.256***	0.030
Pseudo R2	0.098	

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Table 4: Effect of subsidy on Farm Productivity using OLS model

	Ln Catch-up		Ln Frontier Shift		Ln Malmquist index	
	Reginal fixed effect	**No fixed effect**	**Reginal fixed effect**	**No fixed effect**	**Reginal fixed effect**	**No fixed effect**
Constant	-0.007 (0.218)	-0.046 (0.214)	0.553** (0.274)	0.493* (0.270)	0.583 (0.447)	0.487 (0.437)
Treatment	0.330*** (0.100)	0.320*** (0.100)	-0.270** (0.126)	-0.285** (0.126)	0.083 (0.205)	0.067 (0.224)
Ln non-farm income	0.002 (0.004)	0.002 (0.004)	0.001 (0.005)	0.001 (0.005)	0.003 (0.004)	0.004 (0.008)
Ln age	0.014 (0.049)	0.021 (0.048)	-0.102 (0.062)	-0.082 (0.100)	-0.100 (0.100)	-0.082 (0.100)
Ln family size	-0.033 (0.021)	-0.032 (0.021)	-0.034 (0.027)	-0.062 (0.043)	-0.067 (0.043)	-0.062 (0.043)
Lngovernment payment	-0.031*** (0.010)	-0.030*** (0.010)	0.012 (0.062)	0.493* (0.269)	-0.021 (0.021)	-0.018 (0.021)
Region1	-0.009 (0.024)	-	-0.012 (0.030)	-	-0.021 (0.048)	-
Region2	-0.011 (0.024)	-	-0. 020 (0.030)	-	-0. 032 (0.049)	-
Region3	0.044 (0.043)	-	0.050 (0.053)	-	0.087 (0.087)	-
Region4	-0.009 (0.021)	-	-0.029 (0.026)	-	-0.037 (0.043)	-
Region5	0.009 (0.064)	-	0.020 (0.079)	-	0.046 (0.128)	-

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01