May, 2015

Productivity and Efficiency of U.S. Field Crop Farms:

A Look at Farm Size and Operator's Gender[1]

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Selected Paper prepared for presentation at the 2015 Agricultural & Applied Economics Association and Western Agricultural Economics Association Annual Meeting, San Francisco, CA, July 26-28 2015

[1] The views expressed herein are those of the authors, and not necessarily those of the U.S. Department of Agriculture.

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Abstract

This study adopts a stochastic input-oriented distance function to measure technical efficiencies as well as inefficiency determinants, with a closer look at the operator's gender and farm size, for U.S. field crop family farms. The study draws data from USDA's 2013 Agricultural Resource Management Survey. The results show operator's farm size, in terms of total value of production and in terms of operated land acreage, significantly impacts farm's technical efficiency and thus productivity performance, while operator's gender does not. In addition, the study finds that operator's education enhances farm's technical efficiency while a higher diversified production portfolio between crops and livestock production does not statistically impact farm's technical efficiency.

Keywords: Agricultural Resource Management Survey (ARMS), productivity, technical efficiency, stochastic input distance function, U.S. field crop farm

JEL codes: Q12, Q16

I. Introduction

U.S. agricultural productivity growth has been strong in the post-WWII period. Since 1948, U.S. total agricultural output more than doubled with crop production growing faster than livestock production. The share of total farm production revenue attributed to crops increased from 52 to 56 percent between 1948 and 2011 (Wang et. al. 2015). Although there is a rich body of literature on evaluating U.S. agricultural productivity, most of them are either from the perspective of aggregate level (Ball et al. (2004)), or on livestock production (Key and McBride (2003), Mosheim and Lovell (2009), MacDonald and Wang (2011), Key and Sneeringer (2014)), or on commodity-based crop yield analysis. There is a lack of studies on measuring crop farm productivity. While crop yield analysis can provide land productivity information, it is a partial productivity measure and cannot provide information on overall farm productivity performance.

U.S. crop farms have undergone a complex set of structural changes over the last few decades with acreage shifting to larger farms, mid-size farms declining, and farm numbers growing at the extreme—large and small (MacDonald et al. 2013). According to Hoppe (2015), small family farms now account for 89% of the total number of farms in the U.S., and yet, the total value of production of those farms is only 26% of total farm production. Since the number of small farms and large farms both increased in the crop farm sector, it is important to understand how crop farm productivity varied between different sizes of farms and how farm size affects crop farm productivity. While there is evidence showing that farm size is positively linked to agricultural productivity (Feder (1985), Yee et al. (2004), Sumner (2014)), it is unclear how productivity varies among different farm typologies.

The role of rural women in agricultural development has received much academic attention since the launch of the United Nations Decade for Women Program in 1976. While there is a large amount of literature on the economic activities of rural women, most of the studies are based on data from less developed countries (Moock (1976), Udry et al. (1995)). The major argument regarding women's lower economic performance is that women farmers usually have lower levels of human and physical capital that could result in lower productivity or are unable to respond to economic incentives. However, since women farm operators are better educated, on average, than their male counterparts in the U.S. (Hoppe and Korb, 2013) and capital density is much higher in U.S. farm production than in less-developed countries, whether or not women farmers are less productive than their male counterpart in the U.S. farm sector is not clear. Since the share of farms operated by women in the U.S. farm sector has also grown (Hoppe and Korb, 2013), the potential gender inequality regarding economic performance is also important.

This study aims to measure crop farm productivity and efficiency with a closer look at the operator's gender and farm size's impacts. Since field crop harvested acres account for 96% of all crops, and 63% of total crop revenue in 2007 (MacDonald et al.2013), and because of broad differences in production techniques between field crops and vegetables or fruit and nuts, this study only focuses on field crop production. The objectives of this study are three-fold: 1) measure U.S. field crop farm's productive efficiency performance; 2) examine the impacts of farm size and operator's gender on field crop farm's productive efficiency; and 3) examine the efficiency differences between different types of farms.

II. Methodology

There are two popular approaches in measuring technical efficiencies. One is data envelopment analysis (DEA) method developed by Boles (1966), Afriat (1972), and Charnes, Cooper and Rhodes (1978), and another one is stochastic production frontier (SPF) approach initiated by

Aigner, and Scmidt (1977) and Meeusen and van den Broeck (1977). While DEA has the advantage that one does not need to choose a specific functional form or distributional form for the error terms, stochastic frontier approach (SFA) allows for accounting for the data noise. In addition, in the DEA practice we need to utilize a two-stage approach to measure the inefficiency first and then conduct the second-stage regression model analysis using those efficiency estimates from the DEA. Under the SFA framework we are able to incorporate an error components model simultaneously estimated with the SPF function using maximum likelihood (ML) method (Kumbhakar, Ghosh and McGuckin (1991), Reifschneider and Stevenson (1991), and Huang and Liu (1994)). Since our purpose is to evaluate farm-level production performance and inefficiency determinants in the same time, a one-step stochastic frontier approach is preferable.

Since we are measuring a multi-output and multi-input technology for U.S. field crop farms, a frontier production function with one output cannot meet our need. Färe (1988), Färe and Primont (1990), and Färe et al. (1994) have introduced a concept of output-oriented and input-oriented distance functions that allow for measuring multi-input and multi-output technology. Lovell et al. (1994) further developed a stochastic distance function (SDF) framework that has been applied or extended by many others (Grosskopf et al. (1997), Coelli and Perelman (1999), Battese and Coelli, Paul et al. (2004)). Following Färe and Primont (1990), Lovell et al. (1994), and Paul et al. (2004), we define an input-oriented stochastic distance function with multi-input and multi-output technology.

Let $\boldsymbol{x}$ denote the input vector and **y** denote the output vector. A farm's technology can be represented by a set $T = \{(\boldsymbol{x}, \boldsymbol{y}): \boldsymbol{x} \in \boldsymbol{R}^{+}, \boldsymbol{y} \in \boldsymbol{R}^{+}, \boldsymbol{x} \textit{ can produce } \boldsymbol{y}\}$. The input requirement set $L(\boldsymbol{y}) = \{\boldsymbol{x}: (\boldsymbol{x}, \boldsymbol{y}) \in T\}$ represents the production frontier with the set of all input vectors $\boldsymbol{x}$ that can produce $\boldsymbol{y}$ vector. Färe and Primont (1990) shows that the input distance function can be defined as the minimum possible input levels for producing a given output vector while allowing deviation from the frontier:

$$D^i\,(\mathbf{x}, \mathbf{y}) = max\{\rho\!: (\mathbf{x}/\rho) \in L(\boldsymbol{y})\} \quad (1)$$

We estimate a stochastic input-oriented distance function by imposing linear homogeneity in inputs through inputs normalization that $D^I(X,Y)/X_1=D^I(X/X_1,Y)=D^I(X^*,Y)$ (Lovell et al. (1994), Fare and Primont (1995), Kumbhakar et al. (2007)). We approximate the input distance function with the following form:

$$ln(\frac{D_i^I}{X_{1,i}}) = \alpha_0 + \sum_m lnx_{mi}^* + \sum_n lny_{ni} + v_i \quad (2)$$

Equation (2) can be rearranged as:

$$-lnx_{1,i} = \alpha_0 + \sum_m \alpha_m lnx_{mi}^* + \sum_n \beta_n lny_{ni} + v_i - ln\, D_i^I$$

$$=\alpha_0 + \sum_m \alpha_m lnx_{mi}^* + \sum_n \beta_n lny_{ni} + v_i - u_i \quad (3)$$

where x_1 is land that is used to normalize all other inputs, m the inputs, n the outputs, i the farm, $\alpha_0, \alpha_m, and\ \beta_n$ are parameters to be estimated, v_i are random error terms with independently and identically distribution (i.i.d.)$\sim N(0, \sigma_v^2)$, and u_i , the inefficiency components, are nonnegative random variables with independently truncated at zero of the N(μ_i, σ_u^2) distribution, and

$$\mu_i = \boldsymbol{z}_i \boldsymbol{\delta} \quad (4)$$

where $\boldsymbol{z_i}$ is a vector of farm efficiency determinants, and $\boldsymbol{\delta}$ is a vector of estimated parameters. We employ maximum likelihood method (Battese and Coelli (1992)) to estimate the error component model. Since the predicted input distance value $\hat{u}^+ =$

$E[u^{+}|e]$ will be greater or equal to one, Kumbhakar et al. (2007) suggests to use its inverse as the input-oriented technical efficiency (ITE) measure, an equivalent to Farrell (1957)'s input-oriented technical efficiency.

$$\widehat{ITE} = \frac{1}{exp(\hat{u}^{+})} \qquad (5)$$

Since we use cross-section data in the study the technology is treated as given in the year the data were collected (2013) and thus we do not include productivity shifter in the frontier equation. The impact of each efficiency determinant can be measured by its corresponding coefficient.

III. Data

In our study we only look at family farms defined by USDA (Hoppe and MacDonald (2013)). We also exclude three types of farms from the pool of family farms, including retirement farms, off-farm occupation farms, and those with gross cash farm income less than \$100,000 to focus on more commercial-oriented farms. The primary source of data is the 2013 Agricultural Resource Management Survey (ARMS), which is jointly administered by the National Agricultural Statistics Service (NASS) and the Economic Research Service (ERS), USDA. The ARMS covers U.S. farming operations in the 48 contiguous States.

Since we are measuring productivity efficiency at farm level we need to consider all outputs produced from the farm and all inputs used in the farm's production or related activities. In our multi-output and multi-input distance function measurement we include ten inputs—land, labor, capital, seed, contract labor, custom machinery work, agricultural chemical, energy, purchased livestock expense, and working capital—and sixteen outputs—barley, corn, corn for silage, cotton, hay, oats, peanut, other oilseed, rice, sorghum, soybean, tobacco, wheat, other crops, livestock, and other farm related income. The values of output and input variables are referred to as the volume of production or inputs. We utilize volume of production for twelve major field crops. Since only cash value received are collected for livestock, other crops, and other farm related income and no proper price indices are available to adjust farm level production value, we use those cash values directly as the measures of corresponding output variables. Land is measured as operated land acreage, labor is measured as total labor hours, capital is measured as capital depreciation. Since ARMS only collects expenses for all other inputs we use the value of expense as the measure of all other input variables.

To understand how operator's gender and farm size affect farm's productive efficiency, we use data on primary operator's gender from ARMS. We choose two alternative measures to represent the farm size variable—total value of production vs. total acreage of operated land area—and make comparison. Since literature suggest education and production diversity can also attribute to production efficiency, we include these two variables in our model specification as control variables.

Data description

Based on our selection criteria the sample contains a total of 4654 observations (table 1). We group the sample farms by their production specialty (the value of production of one specific commodity exceeds 50 percent of total value of farm production). If there is no single commodity dominating the farm production, but if there is a mix of cash grains production that accounts for more than 50 percent of total value of farm production the farm is defined as general cash grain farm. Otherwise, if the value of all kinds of field crops account for more than 50 percent of total value of production it is defined as a general crop farm.

In our sample, the minimum land acreage is 2 acres and the maximum is 49,600 acres. Since we only look at farms with more than \$100,000 total value of production, the minimum farm production value is \$100,000 and the maximum is \$33,000,000. In general, the number of corn farms accounts for more than one-third of total number of field crop farms. The mean operated land area for wheat, cotton and grain sorghum farms are all more than 2,000 acres while the variation is larger for wheat farms than for the other two. On the other hand, corn and peanut farms have the highest mean and median total value of production with higher variation for corn farms than for the peanut farm.

The number of male operated farms is about 56 times of the number of female operated farms in our sample. The percentage of college graduates is slightly higher for female operators than for their male counterparts (table 2). MacDonald et al. (2013) shows that 73 percent of U.S. crop farms specialized only in crops, while twenty-seven percent of crop production occurred on farms that also had livestock. They indicate that the incidence varied across commodities[3]. In our sample the average livestock's share in total value of production is low for all type of farms, between 1% and 15%, with general cash grain and general crop farms having higher livestock ratio (table 3). We construct a simple diversity index, *DI*, to capture the crop-livestock production diversity of the field crop farms:

Let S_C denote the share of the value of crop production, S_L, the share of the value of livestock production, and *DI*, the diversity index that

$$DI = (S_C * S_L)/(0.5*0.5) \qquad (6)$$

[3] MacDonald et al. (2013) indicates that barley, hay, oats and sorghum producers frequently raise livestock (usually cattle), while little fruit and nut, greenhouse, sugar, rice, or vegetable production occurred on farms with livestock.

If a farm specialized in crop production without producing any livestock, then DI=0. If the farm has a complete diverse production portfolio with crop and livestock production each accounting for 50% of the value of total production, then DI=1. Therefore, a higher diversity index represents a higher diversity in terms of crop-livestock product portfolio.

IV. Empirical Results

Farm size, operator's gender, operator's education attainment, and production diversity

The input distance function and inefficiency determinants regression are estimated simultaneously using STATA with a maximum likelihood (ML) approach. We report the parameter estimates of the stochastic input distance function in appendix table A1. Twenty-three out of twenty-six parameters are significant at 5% level. The results of inefficiency decomposition are reported in table 4. A negative sign of the coefficient indicates the corresponding variable can help reduce the inefficiency distance from its production frontier.

In the literature there are two popular measurements regarding farm size—land acreage vs. value of production. In our empirical estimation, the farm size variable is measured as total operated land acreage for each farm in model 1, while it is measured as total value of production in model 2. In both models farm size significantly impacts inefficiency variable negatively with the implication that larger farm size moves a farm's production performance towards its production frontier and results in higher technical efficiency. Technology development in favor of large scale crop farm production (Schimmelpfennig et al. (2011)) could also play a significant role in advancing large farm technical efficiency.

The operator's gender is measured as a dummy variable with 0 denoting 'male operator' and 1 denoting 'female operator'. Although the coefficients of operator's gender also have negative signs in both models, they are insignificant. Therefore, there is no statistical evidence showing different performance between male and female operated farms in U.S. field crop production.

Literature has shown that higher education can advance human capital and therefore enhance farm production performance. A diversified production portfolio can also improve efficiency by utilizing inputs set to their uttermost usage. However, MacDonald et al. (2013) shows that U.S. crop farms have become more specialized by separating crop production from livestock production. Therefore, in our empirical models we also control for operator's education attainment and production diversity. Education attainment has four levels with 1 indicating the lowest level—that an operator has less than high school education attainment, and 4 indicating the highest level—that operator has 4 years college or more. The sign of education is negative and is significant at 1% level in both models. It implies that a farm operated by a higher educated operator is more technically efficient than other farms.

The coefficients of diversity variable (a higher score indicates a higher diversity in the farm's production portfolio between crop and livestock production) in the two models have different signs, but they are both insignificant at 10% level. It implies that diversified production portfolio between crops and livestock production does not necessarily enhance field crop farm's technical efficiency. Maybe it is also the reason that U.S. crop farms have become more specialized in crop production as indicated by MacDonald eta al. (2013).

Input technical efficiency comparison-by farm typology and by farm specialty

If we group all observations' efficiency scores (based on Model 1) by USDA farm typology (table 5), the results show that the average input technical efficiency score of very large farms (gross cash farm income (GCFI) is more than five million dollars) is nearly three times that of low-sale (small[4]) farms (GCFI is less than 150, 000). However, within the low-sale group there are still farms located in the production frontier with efficiency score of 1. Within the very-large farm group there are also inefficient farms with 0.16 efficiency score. Notwithstanding, according to the median efficiency score, at least more than half of the very large farms are located in the frontier while at least 50 percent of low-sale farms have efficiency scores lower than 0.28. Overall, the efficiency scores are widely distributed and highly deviated from its mean for small farms and are more centralized to its mean for large and very large farms (table 5).

We also group efficiency scores by farm type for states within four USDA production regions—Corn Belt, Lake States, Northern Plains, and Southern Plains[5]—that have more homogeneous geo-climate characteristics and production profile (table 6). We exclude cotton farms due to their smaller farm numbers and ARMS data confidentiality concern. In general, corn farms have the highest mean efficiency score and the second highest in median efficiency score in model 1, while general crop farms rank first in mean and median efficiency scores in model 2 followed by corn farms. General cash grain farms rank the third in either mean efficiency score or median efficiency score in both models. Since general crop farms and general cash grain farms are farms with higher diversity in crops production portfolio, it seems that diversity between crop and livestock production may not benefit crop farm's technical efficiency but diversity within crops production could benefit the farm's productivity performance.

[4] "Small farm" can be defined in different ways according to alternative criteria (Newton, 2014). In this study the definition of small farm is based on USDA's farm typology (Hoppe and Macdonald (2013)) for those passing the threshold of $100,000 total value of production in our sample.
[5] The states included in those regions are OH, IA, MO, IN, MN, MI, WI, ND, SD, KS, NE, TX, and OK.

V. Conclusion

This study adopts a stochastic input-oriented distance function approach to measure technical efficiencies as well as inefficiency determinants, with a closer look at the operator's gender and farm size for U.S. field crop family farms. The study draws data from USDA's 2013 Agricultural Resource Management Survey. The results show that operator's farm size, in terms of total value of production or in terms of operated land acreage, significantly impacts farm's technical efficiency and thus productivity performance. However, an operator's gender does not. In addition, the study finds that a higher educational attainment of the primary operator enhances farm's technical efficiency while a higher diversified production portfolio between crops and livestock production does not impact a farm's technical efficiency.

After controlling for farm size and operator's education characteristics, the results show that corn farms and general crop farms are among the top two in productivity performances, followed by general cash grain farms. It seems that diversified production within different crops could benefit a farm's technical efficiency. This is consistent with literature that diversity could enhance overall productive performance. Yet, based on our results, the diversity needs to be within crop production instead of between crops and livestock production.

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Table 1 Descriptive statistics by crop farm specialty

Specialty	Number of Farms	Mean	Minimum	Median	Maximum	Standard deviation	Coefficient of variation
Operated land acreage							
Corn	1825	1,090	77	755	18,673	8,710	7.99
Cotton	231	2,239	240	1,464	11,200	7,913	3.53
General cash grain	789	1,584	116	900	49,600	14,005	8.84
General crop	465	1,895	2	720	30,300	24,022	12.68
Grain sorghum	34	2,165	300	1,910	8,158	9,824	4.54
Peanut	127	1,233	140	960	5,756	2,249	1.82
Rice	443	921	77	506	11,000	3,192	3.47
Soybean	498	993	101	630	16,000	5,660	5.70
Tobacco	68	743	115	558	5,100	2,972	4.00
Wheat	174	3,165	240	2,100	22,500	26,514	8.38
Sum	4654						
Total value of farm production							
Corn	1825	866868	100178	558065	17976500	7634758	8.81
Cotton	231	859953	105235	489942	3815000	2867723	3.33
General cash grain	789	778988	100888	430250	20605531	6316767	8.11
General crop	465	771554	100000	351818	33000000	7158487	9.28
Grain sorghum	34	434312	100840	263728	1262744	2009989	4.63
Peanut	127	863043	119560	509603	4642934	2111111	2.45
Rice	443	636787	101259	419428	10060058	2024342	3.18
Soybean	498	538516	101150	297360	11353063	3556875	6.60
Tobacco	68	666189	118108	519834	6532085	3112158	4.67
Wheat	174	483969	102021	362408	2955000	3249142	6.71
Sum	4654						

Source: authors' calculation based on ARMS data.

Table 2 Education status by operator's gender

Education attainment	Male				Female			
	Observations	percentage	farms	percentage	Observations	percentage	farms	percentage
Less than high school	114	2.1%	4345	2%	1	1.0%	32	1%
Completed high school	2076	38.3%	87263	39%	32	33.0%	2001	38%
Some college	1704	31.4%	73730	33%	26	26.8%	1359	26%
4 years college or more	1525	28.1%	57591	26%	38	39.2%	1820	35%
Sum	5419	100.0%	222929	100%	97	100.0%	5212	100%

Source: authors' calculation based on ARMS data.

Table 3 Field crop farm's diversity index

Specialty	Observations	Livestock share	diversity index
Corn	1825	2%	0.10
Cotton	231	4%	0.14
General cash grain	789	15%	0.50
General crop	465	12%	0.41
Grain sorghum	34	3%	0.12
Peanut	127	2%	0.09
Rice	443	1%	0.05
Soybean	498	2%	0.09
Tobacco	68	5%	0.18
Wheat	174	7%	0.28

Source: authors' calculation based on ARMS data.

Table 4. Decomposition of input technical inefficiency

Dependent variable: $ln\sigma_u^2$	Model 1 coefficient	Model 1 standard error	Model 1 P>|z|	Model 2 coefficient	Model 2 standard error	Model 2 P>|z|
constant	1.882	0.125	0	1.645	0.133	0
operator's gender(male=0 female=1)	-0.043	0.227	0.850	-0.055	0.225	0.807
farm size[1]	-0.002987	0.000095	0	-0.0000034	0.0000002	0
operator's education	-0.067	0.040	0.089	-0.198	0.042	0
production diversity	0.225	0.141	0.109	-0.164	0.144	0.253

Note: farm size in model 1 is measured as operated land acreage; farm size in model 2 is measured as total value of farm production.

Table 5. Efficiency scores by farm typology (Model 1)

Farm typology	Observations	Mean	Minimum	Median	Maximum	Standard Deviation	Coefficient of Variation
Low-sale[1]	424	0.37	0.03	0.28	1.00	0.24	0.66
Moderate-sale[2]	822	0.46	0.01	0.42	1.00	0.23	0.50
Midsize[3]	1788	0.63	0.03	0.62	1.00	0.22	0.34
Large[4]	1508	0.87	0.04	0.92	1.00	0.15	0.17
Very large[5]	114	0.97	0.16	1.00	1.00	0.11	0.11

Notes:

1. if gross cash farm income (GCFI) is less than 150,000;

2: if $150,000≤GCFI<$350,000;

3: if $350,000≤GCFI<$1,000,000;

4: if $1,000,000≤GCFI<$5,000,000;

5: if GCFI≥$5,000,000

Table 6. Efficiency scores by farm specialty in core regions[1]

Specialty	Observations	Mean	Minimum	Median	Maximum	Standard deviations	Coefficient of Variation
Model 1							
Corn	985	0.534	0.046	0.503	1	1.822	3.41
General cash grain	207	0.495	0.099	0.455	1	1.787	3.61
General crop	17	0.516	0.243	0.504	0.996	1.253	2.43
Rice	20	0.396	0.205	0.223	1	0.792	2.00
Soybean	150	0.469	0.052	0.454	1	1.550	3.30
Sum	1379						
Model 2							
Corn	985	0.595	0.048	0.582	1	1.770	2.98
General cash grain	207	0.520	0.112	0.497	1	1.687	3.25
General crop	17	0.597	0.248	0.652	0.863	1.221	2.05
Rice	20	0.462	0.263	0.264	1	0.854	1.85
Soybean	150	0.477	0.057	0.462	1	1.358	2.85
Sum	1379						

Note: core regions include states located in the following USDA production regions--corn belt, lake states, northern plains, and southern plains, which include OH, IA, MO, IN, IL, MN, MI, WI, ND, SD, KS, NE, TX, and OK fourteen states.

Appendix table A1. Input distance frontier parameters

	Model 1			Model 2		
Dependent variable:-*ln(land)*	coefficient	standard error	P>|z|	coefficient	standard error	P>|z|
constant	-6.634	0.057	0	-6.7867	0.0658	0
ln(labor)	0.074	0.005	0	0.0858	0.0050	0
ln(capital)	-0.017	0.004	0	-0.0123	0.0039	0.002
ln(seed)	0.047	0.008	0	0.0495	0.0087	0
ln(contract labor expense)	0.014	0.002	0	0.0178	0.0023	0
ln(custom machinery work)	0.008	0.002	0	0.0108	0.0018	0
ln(chemicals)	0.055	0.008	0	0.1191	0.0101	0
ln(livestock expense)	0.060	0.004	0	0.0748	0.0039	0
ln(energy)	0.005	0.010	0.613	0.0243	0.0099	0.014
ln(other working capital)	0.011	0.006	0	0.0237	0.0060	0
ln(barley)	-0.025	0.006	0	-0.0347	0.0069	0
ln(corn)	-0.018	0.002	0	-0.0128	0.0021	0
ln(corn sileage)	-0.012	0.007	0	-0.0151	0.0073	0.038
ln(cotton)	-0.022	0.002	0	-0.0280	0.0022	0
ln(hay)	-0.015	0.004	0	-0.0208	0.0046	0
ln(oats)	0.017	0.007	0	0.0090	0.0078	0.248
ln(other oilseed)	-0.010	0.009	0	-0.0185	0.0109	0.090
ln(peanut)	0.000	0.002	0.952	-0.0019	0.0024	0.430
ln(rice)	-0.032	0.002	0	-0.0327	0.0024	0
ln(sorghum)	-0.013	0.003	0	-0.0243	0.0035	0
ln(soybean)	-0.010	0.002	0	-0.0152	0.0024	0
ln(tobacco)	-0.002	0.004	0.529	0.0017	0.0041	0.673
ln(wheat)	-0.016	0.002	0	-0.0222	0.0019	0
ln(livestock)	-0.057	0.003	0	-0.0708	0.0037	0
ln(other crops	-0.018	0.002	0	-0.0125	0.0026	0
ln(farm related income)	-0.050	0.003	0	-0.0585	0.0031	0
Wald X^2	1910			2986		
Log-likelyhood	-3220			-3756		
number of observations	4654			4654		