The Impacts of Off-Farm Income on Farm Efficiency, Scale, and Profitability Rice Farms

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Abstract
This paper estimates technical efficiency on rice farms, following a translog stochastic production frontier (SPF) approach and compares the relative performance of farm operator households with and without off-farm wages and salaries. We use 2000, 2006 and 2013 USDA data for rice producing states-identifying different performance measures. Previous studies suggest that off-farm work influences economic performance—by "improving" managerial performance. We find that off-farm income generally boosts scale and technical efficiency on smaller, mid-size and larger operations, and is also consistent with higher farm and household returns. We also find that the number of hours worked off-farm by the operator contributes to a higher technical efficiency on larger typologies.

Introduction

Made possible by alternative employment opportunities and facilitated by labor-saving technological progress, such as mechanization, off-farm work by farm operators and their spouses' has risen steadily over the past decades, becoming the most important component of farm household income (Mishra et al.) According to a USDA report, total net income earned by farm households from farming grew from about $15 billion in 1969 to nearly $50 billion in 1999 and is estimated at $118 billion in 2012. However, off-farm earned income, which began at a roughly comparable figure in 1969 ($15 billion), soared to about $120 billion in 1999 and is estimated at more than $150 billion in 2012. In addition, as women's wages have risen, married women have become more likely to work in the paid labor market and household tasks are now shared between spouses. Moreover, as U.S. farms continue to grow markedly in size, issues related to the interaction of off-farm income, farm size, and economic performance in general are among the leading concerns affecting U.S. agriculture. Because of the controversies surrounding these issues, agricultural economists have been looked to for objective information on these issues.

Background

Despite its considerable importance, and perhaps due to modeling and data challenges, issues related to the impact of off-farm income have been largely neglected (with a few notable exceptions) in studies of farm structure and economic performance in U.S. agriculture. Hence, this paper will: 1) identify the characteristics and location of off-farm earnings on rice farms, 2) develop farm level estimates of technical efficiency with and without off-farm income on rice farms using a Stochastic Production Frontier (SPF) approach, including appropriate environmental information in the Coelli inefficiency effects; and 3) assess the economic implications of structural and environmental change on efficiency on residential, intermediate, and commercial farms producing rice.

In the Appendix (table 1) we present information on rice production and off-farm work reliance over time—from ARMS data for 2000 compared to 2013. We find continued reliance on off-farm work over time and significant changes in chemical use and most significantly, dramatic consolidation of production into larger typologies. Appendix figures 1, 2, and 3 provide details on chemical use over time and by state. This is important as rice production in California is distinct from the rest of the country in many ways as is described in detail below along with changes in seed technology and land use over time and by region.

Rice production costs in California

The nominal costs of major inputs used in rice production; seed, fertilizer, chemicals and land all increased substantially from 2006 to 2013. Seed costs were up about $30 per acre, fertilizer costs were over $50 per acre higher, chemical costs were over $40 per acre higher, and land values were about $2,600 per acre higher. After adjusting for price changes in these inputs during 2006-

13, seed costs were actually $7 per acre lower in 2013, suggesting an improved efficiency of seed technologies and/or seed use. Fertilizer real costs also declined about $3 per acre. But chemical costs remained higher in 2013 than in 2006 even after price levels were adjusted, suggesting that more chemicals were applied to rice acres in California in 2013 than in 2006. And, land values increased substantially in real terms, close to $1,600 per acre, suggesting pressure on land rents. Concomitantly, hybrid seed use remained small at 5 percent or less of acres and use of herbicide resistant seed actually declined from only 4 percent in 2006 to none reported in 2013.

Rice production costs and technical data—California only, 2006 and 2013

Item	2006	2013
Purchased seed		
Production costs, nominal dollars	31.02	61.26
Production costs, 1990-02 dollars[1]	29.26	18.45
Commercial fertilizer		
Production costs, nominal dollars	98.15	149.54
Production costs, 1990-92 dollars[2]	55.77	53.60
Chemicals		
Production costs, nominal dollars	124.58	167.83
Production costs, 1990-92 dollars[3]	97.33	108.28
Land		
Value per acre, nominal dollars	5,996	8,608
Value per acre, 1990-92 dollars[4]	3,382	4,985
Hybrid Seed		
Percent total rice area	5	4
Herbicide Resistance Seed		
Percent total rice area	4	0

[1]2006 and 2013 seed costs are deflated using the national agricultural seed and plant price index (USDA, NASS, Agricultural Prices).
[2]2006 and 2013 commercial fertilize costs are deflated using the national agricultural mixed fertilizer price index (USDA, NASS, Agricultural Prices).
[3]2006 and 2013chemical costs are deflated using the national agricultural total chemical price index (USDA, NASS, Agricultural Prices).
[4]2006 and 2013 land values are deflated using trends for rice states (Agricultural Statistics).
Source: USDA, ERS using data from the 2006 and 2012 Agricultural Resource Management Surveys, and Agricultural Statistics.

Rice production costs in non-California states

The nominal costs of major inputs used in rice production; seed, fertilizer, chemicals and land all increased substantially from 2006 to 2013. Seed costs were up about $20 per acre, fertilizer costs were nearly $70 per acre higher, chemical costs were about $20 per acre higher, and land values were about $1,400 per acre higher. After adjusting for price changes in these inputs during 2006-13, seed costs were actually $5 per acre lower in 2013, suggesting an improved efficiency of seed technologies and/or seed use. Fertilizer and chemical costs remained higher in 2013 than in 2006 even after price levels were adjusted, suggesting that more fertilizer and chemicals were applied to rice areas outside of California in 2013 than in 2006. And land values increased substantially in real terms, close to $900 per acre, suggesting pressure on land rents. Concomitantly, hybrid seed use increased from 12 percent of rice area to 28 percent and use of herbicide resistant seed increased significantly from 24 percent of rice area to 41 percent.

Rice production costs and technical data—excluding California, 2006 and 2013

Item	2006	2013
Purchased seed		
Production costs, nominal dollars	39.97	109.28
Production costs, 1990-02 dollars[1]	37.75	32.92
Commercial fertilizer		
Production costs, nominal dollars	79.38	147.55
Production costs, 1990-92 dollars[2]	45.10	52.89
Chemicals		
Production costs, nominal dollars	71.02	90.79
Production costs, 1990-92 dollars[3]	55.49	58.58
Land		
Value per acre, nominal dollars	1,611	3,069
Value per acre, 1990-92 dollars[4]	909	1,777
Hybrid Seed		
Percent total rice area	12	28
Herbicide Resistance Seed		
Percent total rice area	24	41

[1]2006 and 2013 seed costs are deflated using the national agricultural seed and plant price index

(USDA, NASS, Agricultural Prices).
[2]2006 and 2013 commercial fertilize costs are deflated using the national agricultural mixed fertilizer price index (USDA, NASS, Agricultural Prices).
[3]2006 and 2013chemical costs are deflated using the national agricultural total chemical price index (USDA, NASS, Agricultural Prices).
[4]2006 and 2013 land values are deflated using trends for rice states (Agricultural Statistics).
Source: USDA, ERS using data from the 2006 and 2012 Agricultural Resource Management Surveys, and Agricultural Statistics.

Data and Methods

We use U.S. farm-level data from the rice data from the 2013, 2006, and 2000 ARMS USDA surveys related to the value of output and cost of production in our analysis. The Cost of Production ARMS surveys for rice are done roughly every seven years. The list and area frame components are incorporated using a system of weights. Inferences for the states and regions must account for the survey design by using weighted observations. The farm-level data is used in an innovative way. We define one output : , Gross value of sales on rice farms (),and six inputs: labor, fertilizer, fuel, miscellaneous, capital, and a quality adjusted land input.

We will use regression techniques that allow us to relate several outputs to several inputs in a single equation to develop measures of technical (best practice production techniques) and scale efficiency scores by farm. We use stochastic production frontier (SPF) measurement to econometrically estimate a translog production frontier. We will test for and correct for inputs that are endogenous to the production process.

Methodology

A parametric production function approach is used to estimate performance measures, including RTS and TE. Following Nehring et al. (2006) we estimate a translog production function. For the analysis, output is developed from the ARMS for rice farms are: Y_{Farmin} =

value of total farm production.

To account for differences in land characteristics, state-level quality-adjusted values for the U.S. estimated in Ball et al. (2008) are multiplied by acres operated to construct a stock of land by farm. That is, the estimated state-level quality-adjusted price for each farm is multiplied by actual acres of pasture and non-pasture and a service flow computed based on a service life of 20 years and interest rate of 6%. See Nehring et al. (2006) for a fuller description. Ignoring land heterogeneity, including urbanization effects on productivity and agronomic (i.e., water holding capacity, organic matter, slope, etc., of land) and climatic information incorporating the differing crop and pasture patterns used in dairying, would result in biased efficiency estimates (Ball et al. 2008; Nehring et al. 2006).

Stochastic Production Frontier Models

The parametric stochastic production frontier approach was introduced by Aigner, Lovell, and Schmidt, and Meeusen and van den Broeck. Battese and Coelli modified this approach to specify stochastic frontiers for the technical efficiency effects and simultaneously estimate all the parameters involved. In this paper we follow the model described in Coelli and Battese using STATA. In what follows, we layout the translog approach.

The Translog Approach

The translog functional form of the stochastic production frontier model is defined as

(1) $$\ln Y_{it} = \beta_0 + \sum_{j=1} \beta_j \ln x_{ijt} + 1/2 \sum_{j=1} \sum_{k=1} \beta_{jk} \ln x_{ijt} * \ln x_{ikt} + v_{it},$$

where subscript *i* denotes farms, *j* inputs, and *t* time period.

Technical efficiency is defined as the ratio of the observed output to the frontier output that could be produced by a fully efficient firm. Thus, technical efficiency of a farmer is between zero and one and is inversely related to the inefficiency effect.

We calculate the elasticities of output with respect to each of the inputs. Since output and inputs are all expressed in logarithms, the elasticities can be simply obtained from partial differentiation of the production function with respect to the appropriate inputs. The elasticity, E_{i}, measuring the responsiveness of output to a one percent change in the i^{th} input, is given by

(2) $$E_{,it} = \partial Y / \partial X_{it} = \beta_i + \sum_k \beta_{ikt} X_{kt} .$$

The estimate of returns to scale (RTS), defined as the percentage change in output due to a proportional increase in the use of all inputs, is calculated as the sum of the elasticities.

(3) $$RTS = \sum_i \beta_i .$$

If the estimate is greater than, equal to, or less than unity, the returns to scale in production are classified as increasing, constant, or decreasing, respectively.

Specification of the Translog Approach

The translog functional form of the stochastic production frontier model is defined as

(4) $$\ln Y_{,it} = \beta_0 + \beta_{LB} \ln(X_{LB,it}) + \beta_E \ln(X_{E,it}) + \beta_F \ln(X_{F,it}) + \beta_{MS} \ln(X_{MS,it}) + \beta_K \ln(X_{K,it})$$

$$+ \beta_{LB,LB} (\ln X_{LB,it})^2 + \beta_{E,E} (\ln X_{E,it})^2 + \beta_{F,F} (\ln X_{F,it})^2 + \beta_{MS,MS} (\ln X_{MS,it})^2 + \beta_{K,K} (\ln X_{K,it})^2$$

$$+\beta_{LD,LD}(\ln X_{LD,it})^2+\beta_{LD}\ln(X_{LD,it})+\beta_{LB,E}\ \ln X_{LB,it}\ln X_{E,it}+\beta_{LB,F}\ \ln X_{LB,it}\ln X_{F,it}$$

$$+\beta_{LB,MS}\ \ln X_{LB,it}\ln X_{MS,it}+\beta_{LB,K}\ \ln X_{LB,it}\ln X_{K,it}+\beta_{LB,LD}\ \ln X_{LB,it}\ln X_{LD,it}$$

$$+\beta_{E,F}\ln X_{E,it}\ln X_{F,it}+\beta_{E,MS}\ln X_{E,it}\ln X_{MS,it}+\beta_{E,K}\ln X_{E,it}\ln X_{K,it}$$

$$+\beta_{E,LD}\ln X_{E,it}\ln X_{:LD,it}+\beta_{F,MS}\ln X_{F,it}\ln X_{MS,it}+\beta_{F,K}\ln X_{F,it}\ln X_{K,i}$$

$$+\beta_{F,LD}\ln X_{F,it}\ln X_{LD,it}+\beta_{MS,K}\ln X_{MS,it}\ln X_{K,it}+\beta_{MS,LD}\ln X_{MS,it}\ln X_{LD,it}$$

$$+\beta_{K,LD}\ln X_{K,i}t\ln X_{LD,it}+v_{it}-u_{it},$$

where subscripts *i* refer to the i^{th} farmer and *t* represents the time period. Farm output (Y), labor (X_{LB}), fuel (X_{E}), fertilizer (X_{F}), miscellaneous operating expenses (X_{MS}), capital services (X_{K}), and the quality-adjusted price of land (X_{LD}), are all measured as logs of monetary terms. With such monetary measures, the interpretation of efficiency scores likely reflects a mixture of technical and allocative efficiency, given some level of allocative inefficiency.

Finally, TE "scores" are estimated as TE = exp($-u_{\mathrm{it}}$). Impacts of changes in R_{q} on TE can also be measured by the corresponding δ coefficient in the inefficiency specification for $-u_{\mathrm{it}}$. It is assumed that the inefficiency effects are independently distributed and u_{it} arise by truncation (at zero) of the exponential distribution with mean μ_{it}, and variance σ^2.

The Empirical Results

The parameter estimates for the rice model are reported in Table 1.

As shown in table 2 the input elasticity measures show strong scale economies with size.

Technical efficiency also increases with farm size on rice farms. Comparing typologies with earned income and without we generally find that off-farm income boosts scale and technical efficiency for rice farms and also boosts farm and household returns.

Summary and Concluding Remarks

This study examines the economic impact of off farm income and environmental factors on economic performance in key rice-producing states. It uses a translog stochastic production frontier approach to evaluate the scale and technical efficiency of small independent as compared to large farming operations, and the additional productive and thus competitive contributions of off-farm income (both operator and spousal). We correct for endogeneity of the hours worked off farm by the operator and spouse as they are modeled in the Coelli inefficiency effects. Based on previous related research we expect the SPF analysis to reveal that the economic impact of off-farm is likely to vary considerably across the subset of rice farms considered over the 2000-2013 period, and, in general, boasting the efficiency of smaller-scale operations.

As U.S. farms continue to grow markedly in size, issues related to the interaction of off-farm income, farm size, and economic performance in general are among the leading concerns affecting U.S. agriculture (see Appendix Table 1). Because of the controversies surrounding these issues, agricultural economists have been looked to for objective information on these issues. Despite its considerable importance, and perhaps due to modeling and data challenges, issues related to the impact of off-farm income have been largely neglected (with a few notable exceptions) in studies of farm structure and economic performance in U.S. agriculture.

Based on preliminary results, we find that the economic impact of off-farm work to vary considerably across the type of farm and across typology. Most importantly, we find that off-farm income generally boosts scale efficiency and household and own farm profitability on rice farms across typologies. We also find that operator hours worked off farm positively impact technical efficiency on corn farms. We attribute these results in the whole farm production function estimated to a positive and statistically significant impact on technical efficiency by operator labor off-farm (i. e. the production system is managed more efficiently in the sense of getting more output from the same level of inputs on such farms with operators working off-farm and the primal measure is altered influencing the measure of scale efficiency). More precisely, we hypothesis that managerial labor is "improved" by the off-farm hours that are used to boost household income, often in work environments that improve managerial skills. Cropping patterns have changed significantly over the time period analyzed due to new seed technology, thus altering the composition and level of pesticides and fertilizer used.

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Table 1. ML Estimates of the Stochastic Translog Production Frontier for 2000, 2006, and 2013 pooled data

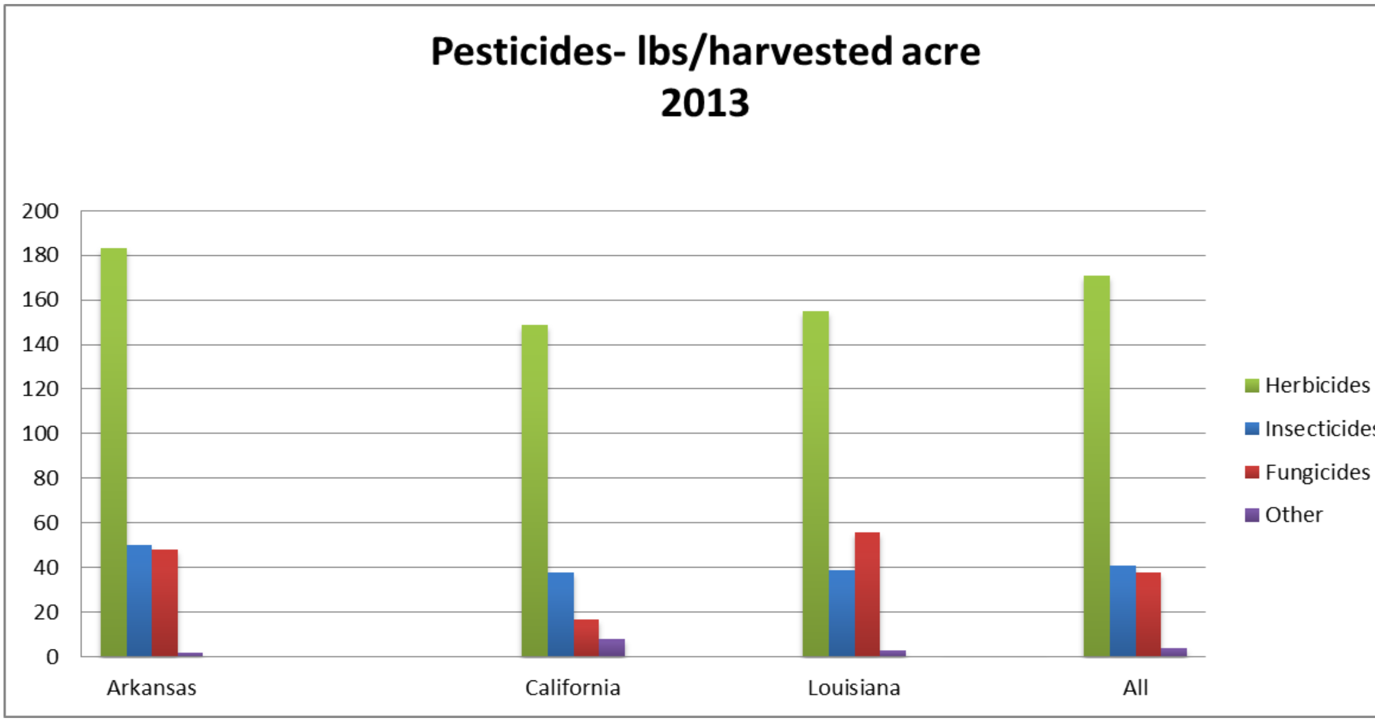
Variable	Parameter	t-test	Variable	Parameter	t-test
β_0	12.728***	(3.95)	β_{XF*XK}	0.030	(0.39)
β_{XLB-}	-1.574***	(-3.49)	β_{XF*XLD}	-0.117*	(-2.03)
β_{XE}	0.469	(1.21)	β_{XMS*XK}	-0.354**	(-2.61)
β_{XF}	1.705***	(4.89)	$\beta_{XMS*XLD}$	0.161*	(2.31)
β_{XMS}	-0.835	(-1.02)	β_{XK*XLD}	0.121	(1.07)
β_{XK}	-0.073	(-0.09)	$\beta_{year2013}$	0.522***	(8.81)
β_{XLD}	-0.549	(-0.96)	$\beta_{California}$	0.324***	(4.74)
$\beta_{XLB*XLB}$	0.007	(0.85)	δ_0	-2.568***	(-10.57)
β_{XE*XE}	-0.001	(-0.07)	δ_{UI}	-2.139	(-1.32)
β_{XF*XF}	0.009	(1.01)	δ_{Popacc}	-0.547*	(-2.11)
$\beta_{XMS*XMS}$	0.011	(0.21)	$\delta_{Off-FarmOp}$	-0.300*	(-2.34)
β_{XK*XK}	0.341**	(2.32)	$\delta_{Off-FarmSp}$	0.006	(0.36)
$\beta_{XLD*XLD}$	-0.049	(-1.18)	δ_{Age}	0.253	(0.63)
β_{XLB*XE}	0.062	(1.60)	$\delta_{Year2013}$	1.356*	(2.68)
β_{XLB*XF}	-0.068*	(-1.88)	$\delta_{California}$	1.105***	(4.50)
$\beta_{XLB*XMS}$	0.245***	(3.12)	δ_v	0.277***	(9.67)
β_{XLB*XK}	-0.137	(-1.49)			
$\beta_{XLB*XLD}$	-0.001	(-0.01)			
β_{XE*XF}	0.100*	(1.96)			
β_{XE*XMS}	0.147*	(1.81)	Observations	1,510	
β_{XE*XK}	-0315***	(-3.21)	Number of replicates	17,041	
β_{XE*XLD}	-0.036	(-0.66)	Efficiency Score	0.608	
β_{XF*XMS}	-0.085***	(-3.15)			
Input elasticities					
Labor	0.109				
Fuel	0.056				
Fertilizer	0.071				
Miscellaneous	0.156				
Capital	0.423				
Land	0.266				
RTS	1.080				

Note: Three asterisks indicate significance at the 1% level (t=2.576), two indicate significance at the 5% level (t=1.96), and one indicates significance at the 10% level =1.645).

Source: Authors' analysis of USDA Agricultural Resource Management Survey Data.

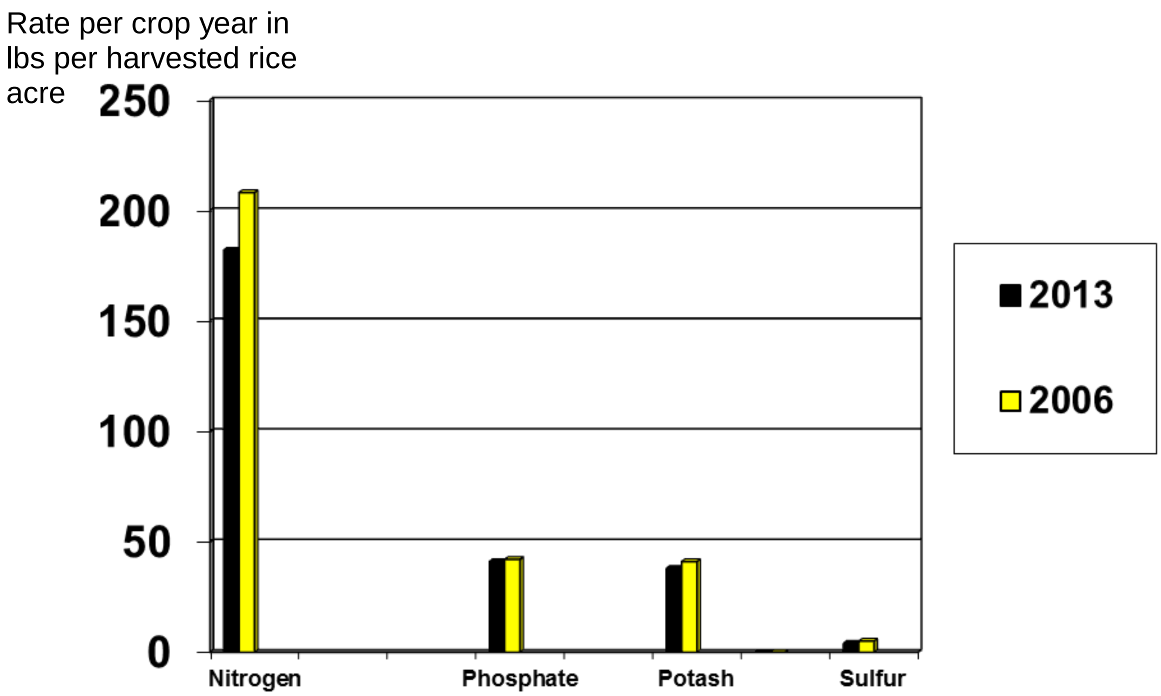
a. The t-statistics are based on jackknifing techniques described in Dubman .

Appendix Figure 1. Pesticide use in Rice Production, by pesticide type.



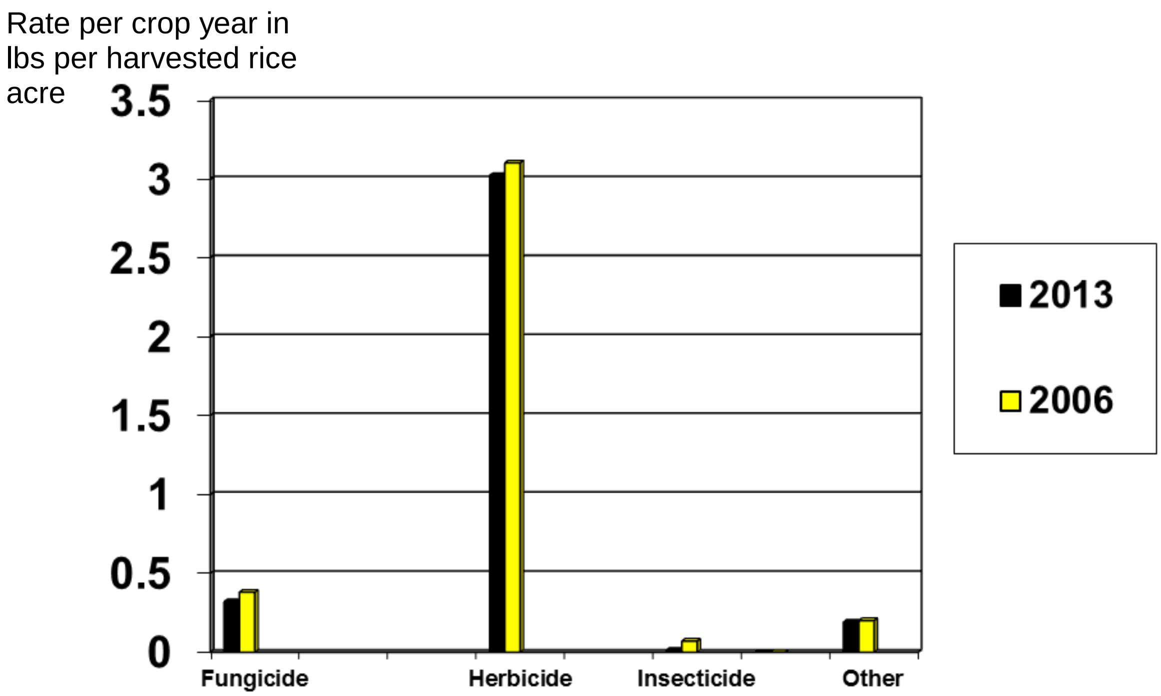
Selected States; omits Mississippi, Missouri, and Texas
Harvested acres approximate planted acres in Rice production
Source: NASS Quick Stats and Agricultural Statistics.

Appendix Figure 2:Fertilizer use by Rice farmers based on Phase II data: 2013 and 2006



Harvested acres approximate planted acres in Rice production
Source: NASS Quick Stats and Agricultural Statistics., selected issues

Appendix Figure 3: Pesticide use by Rice farmers based on Phase II data: 2013 and 2006



Selected States; omits Mississippi, Missouri, and Texas
Harvested acres approximate planted acres in Rice production
Source: NASS Quick Stats and Agricultural Statistics., selected issues

AppendixTable 1. Performance Measures and technical data for Rice Farms by Group: Size, Earned and No Earned Income, 5 States, 2000 and 2013: ERS Farm typologies									
	GROUP								
Item	Retirement Off-farm occupation	Small Farms: No Earned Income	Small Farms: Earned Income	Midsize Farms: No Earned Income	Midsize Farms: Earned Income	Large Farms: No Earned Income	Large Farms: Earned Income	Non Family Corporations	All farms
Rice Household Model									
No observations 2000	20	80	158	47	108	19	26	11	469
% of Farms	6	18	33	10	23	3	4	3	100
% of Valu of Prod	2	10	15	16	28	11	12	6	100
Hybridrice Percent	24	3	10	7	7	12	3	2	8
Fert Exp per rice acre	68	59	67	60	67	45	73	72	65
Owned	40	43	40	56	47	41	46	67	45
Yield	74	64	62	63	67	61	72	71	65
Ophours off-farm	1765	0	224	0	316	0	191	0	260
Sphours off-farm	532	0	872	0	931	0	963	0	569
No observations 2013	11	17	24	70	84	117	157	62	542
% of Farms	14	5	6	12	17	14	22	9	100
% of Valu of Prod	1	1	1	6	8	24	40	18	100
Hybridrice Percent	5	10	15	28	18	34	26	34	22
Fert Exp per rice acre	64	79	69	78	63	75	64	84	71
Owned	10	40	24	25	33	35	22	35	27
Yield	88	72	86	73	78	80	83	81	80
Ophours off-farm	842	0	172	0	322	0	205	0	230
Sphours off-farm	1221	0	1192	0	1238	0	1290	0	758

Table 2. Characteristics of Farms Including Technical Efficiency and Returns to Scale, Rice farms, 2000 to 2013 ARMS COP Surveys.

Item	Group							
	Retirement Off-farm occupation	Small Farms: No Earned Income	Small Farms: Earned Income	Midsize Farms: No Earned Income	Midsize Farms: Earned Income	Large Farms: No Earned Income	Large Farms: Earned Income	Non Family Corporations
No. Obs.	52	109	132	181	198	551	160	127
No. Farms	1,405	1,312	1,451	1,589	1,692	7,289	935	1,359
% Value of Production	1.1	3.3	3.8	10.6	11.2	32.9	22.0	15.1
Rice Acres per Farm	91.96	237.92	292.50	544.22	507.30	443.65	1,011.57	671.13
Acres operated	273.50	847.10	769.64	1,466.90	1,361.25	1,452.07	3,672.31	2,712.64
Yield, bu/ac	73.15	69.61	72.41	72.18	74.17	67.28	79.41	76.56
pesticide/$ per harvested rice ac	85.08	54.89	58.62	67.49	64.97	57.61	70.72	68.11
fertilizer/$ per harvested rice ac	65.27	69.58	73.63	71.48	62.39	55.02	56.51	67.44
Net Return on Assets	0.057	0.041	0.051	0.072	0.099	0.148	0.175	0.065
Household returns	0.097	0.033	0.089	0.069	0.121	0.208	0.243	0.0
Ophours	1,151	0.0	203	0.0	203	0.0	237	0.0
Sphours	902	0.0	1,145	0.0	1,257	0.0	1,257	0.0
Debt-Asset Ratio	0.16	0.08	0.19	0.12	0.15	0.12	0.24	0.15
Technical Efficiency	0.703	0.670	0.637	0.670	0.682	0.691	0.705	0.686
Returns to Scale	1.001	1.041	1.056	1.125	1.121	1.054	1.244	1.184