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

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Selected Poster prepared for presentation at the Southern Agricultural Economics Association (SAEA) Annual Meeting, San Antonio, Texas, February 6-9, 2016.

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 data website, total net income earned by farm households from farming grew in real terms from about $10 billion in 1969 to over $60 billion in 1999 and is estimated at $132 billion in 2014 (USDA 2014). However, off-farm earned income, which began at a roughly comparable figure in 1969 ($6 billion), soared to about $60 billion in 1999 and is estimated at more than $100 billion in 2014. 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 issues of interest affecting U.S. agriculture.

Background

Despite its considerable importance, and perhaps due to modeling and data challenges, issues related to the impact of off-farm income on economic performance measures have been largely neglected (with a few notable exceptions—see Mishra et al 2009) in studies of farm structure and economic performance in U.S. agriculture. Hence, in this paper we will: 1) identify the characteristics and location of off-farm earnings on cotton farms, 2) develop farm level estimates of technical efficiency with and without off-farm income on cotton farms using a Stochastic Production Frontier (SPF) approach, including other factors (e.g. population accessibility, and off-farm hours worked by the operator and spouse) influencing technical efficiency in the Coelli inefficiency effects; and 3) assess the economic implications of structural and environmental change on efficiency on small, mid-size, and large farms commercial farms producing cotton.

In the Appendix (tables 1 and 2) we present information on cotton production and off-farm work reliance over time—from ARMS data for 2002/2008 compared to 2009/2014 and the entire data series . We find continued reliance on off-farm work over time despite 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 cotton production in the Fruitful Rim and (including California) and in the Prairie Gateway (including Texas) is distinct from other producing areas of the country in many ways as is described in detail below in terms of with changes in seed, fertilizer and chemical purchases and to land use over time and by region.

Cotton production costs in the Fruitful Rim including California

The nominal costs of major inputs used in cotton production; seed, fertilizer, chemicals and land all increased substantially from 2005 to 2014. Seed costs were up over $60 per acre, fertilizer costs were over $75 per acre higher, chemical costs were about $20 per acre higher, and land values were about $2,600 per acre higher. Land values increased substantially in real terms, close to $6,000 per acre, suggesting pressure on land rents.

Table 1: Cotton production costs —Fruitful Rim (including California), 2005, 2010 and 2014

Item	2005	2010	2014
Purchased seed			
Production costs, nominal dollars	38.67	83.32	107.15
Commercial fertilizer			
Production costs, nominal dollars	48.91	94.17	125.02
Chemicals			
Production costs, nominal dollars	88.27	95.41	106.01

Land			
Value per acre, nominal dollars	9,350	10,900	12,100
Value per acre, 2002 dollars[1]	4,062	6,640	10,226

[1]2005, 2010, and 2015 land values are deflated using trends for cotton states. Source: USDA, ERS using data from the 2005, 2010, and 2014 Agricultural Resource Management Surveys, and Agricultural Statistics. Farm Resource Regions are defined in USDA 2000.

Cotton production costs in the Prairie Gateway (including Texas)

The nominal costs of major inputs used in cotton production; seed, fertilizer, chemicals and land all increased substantially from 2005 to 2014. Seed costs were up about $40 per acre, fertilizer costs were nearly $40 per acre higher, chemical costs were close to $20 per acre higher, and land values were about $900 per acre higher. And land values increased substantially in real terms, close to $900 per acre, again suggesting pressure on land rents in this region, but on a smaller scale perhaps than in the Fruitful Rim.

Table 2: Cotton production costs —The Prairie Gateway (including Texas), 2005, 2010 and 2014

Item	2005	2010	2014
Purchased seed			
Production costs, nominal dollar	41.19	62.27	80.07
Commercial fertilizer			
Production costs, nominal dollar	15.60	41.60	55.23
Chemicals			
Production costs, nominal dollar	28.15	41.14	45.71
Land			
Value per acre, nominal dollars	1,110	1,680	1,880
Value per acre, 2002 dollars[1]	899	1,415	1,620

[1]2005, 2010, and 2015 land values are deflated using trends for cotton states. Source: USDA, ERS using data from the 2005, 2010, and 2014 Agricultural Resource Management Surveys, and Agricultural Statistics. Farm Resource Regions are defined in USDA 2000.

Data and Methods

We use U.S. farm-level cotton data from the 2002 to 2014 ARMS USDA surveys related to the value of output and cost of production in our analysis. The states covered are Alabama, Arizona, California, Georgia, Louisiana, Mississippi, Missouri, North Carolina, South Carolina, Tennessee, and Texas. The Cost of Production ARMS surveys for cotton are done roughly every five years. The data set consists of 9,233 observations of farms growing some cotton and including small livestock operations; e.g operations with >50 beef or dairy cows were excluded from the analysis. 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 three outputs: Gross value of sales from non-cotton output, cotton output, and off-farm income, and six inputs: labor, fertilizer, fuel, miscellaneous, capital, and a quality adjusted land input. We 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 an input distance function 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 Morrison-Paul and Nehring (2005) and Morrison-Paul et al. (2004a,b), we estimate an input distance production function.

Stochastic Production Frontier Models

A parametric input distance function approach is used to estimate performance measures, including RTS and TE. The input distance function is denoted as $D^I(\boldsymbol{X},\boldsymbol{Y},\boldsymbol{R})$, where $\boldsymbol{X}$ refers to inputs, $\boldsymbol{Y}$ to outputs, and $\boldsymbol{R}$ to other farm efficiency determinants. For the analysis, three outputs developed from the ARMS for cotton farms are: Y_{COT} = value of cotton production, Y_{NONCOT} = value of non cotton crop production and small scale livestock production included in the data, and Y_{OFF} = off-farm income, which is total off-farm income less unearned income. Inputs are costs of: X_{LAB} = labor; X_{CAP} = capital; X_{MISC} = miscellaneous including feed, fertilizer, and fuel; and X_{QLND} = quality adjusted land. Thus, our analysis is whole-farm.

The input distance function represents farms' technological structure in terms of minimum inputs required to produce given output levels, as farmers typically have more short-term control over input than output decisions (Morrison-Paul et al. 2004a,b). Also, Morrison-Paul and Nehring (2005) found output-oriented models to have limitations—a less good fit—when output composition differences are important, as is the case in this cotton survey, designed to include very small cotton farms along with large cotton farms to get population estimates. See Morrison-Paul and Nehring (2005), and Dorfman and Koop (2005), for ARMS applications of distance functions.

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 pasture plus non-pasture acres 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 cotton production, would result in biased efficiency estimates (Ball et al. 2008; Nehring et al. 2006).

Estimating $D^I(\boldsymbol{X},\boldsymbol{Y},\boldsymbol{R})$ requires imposing linear homogeneity in input levels (Färe and Primont 1995), which is accomplished through normalization (Lovell et al. 1994); $\mathrm{D}^{\mathrm{I}}(\boldsymbol{X},\boldsymbol{Y}, \boldsymbol{R})/X_1 = \mathrm{D}^{\mathrm{I}}(\boldsymbol{X}/X_1,\boldsymbol{Y}, \boldsymbol{R}) = \mathrm{D}^{\mathrm{I}}(\boldsymbol{X^*},\boldsymbol{Y}, \boldsymbol{R})$. Approximating this function by a translog functional form to limit *a priori* restrictions on the relationships among its arguments results in:

(1a) $\ln D^I_{it}/X_{1,it} = \alpha_0 + \Sigma_m \alpha_m \ln X^*_{mit} + .5 \Sigma_m \Sigma_n \alpha_{mn} \ln X^*_{mit} \ln X^*_{nit} + \Sigma_k \beta_k \ln Y_{kit}$

$+ .5 \Sigma_k \Sigma_l \beta_{kl} \ln Y_{kit} \ln Y_{lit} + \Sigma_q \phi_q R_{qit} + .5 \Sigma_q \Sigma_r \phi_{qr} R_{qit} R_{rit} + \Sigma_k \Sigma_m \gamma_{km} \ln Y_{kit} \ln X^*_{mit}$

$+ \Sigma_q \Sigma_m \gamma_{qm} \ln R_{qit} \ln X^*_{mit} + \Sigma_k \Sigma_q \gamma_{kq} \ln Y_{kit} \ln R_{qit} + v_{it} = TL(\boldsymbol{X^*},\boldsymbol{Y}, \boldsymbol{R}) + v_{it}$, or

(1b) $-\ln X_{1,it}= TL(\boldsymbol{X^*},\boldsymbol{Y}, \boldsymbol{R}) + v_{it} - \ln D^I_{it} = TL(\boldsymbol{X^*},\boldsymbol{Y}, \boldsymbol{R}) + v_{it} - u_{it}$,

where i denotes farm; t the time period; k,l the outputs; m,n the inputs; and q,r the $\boldsymbol{R}$ variables. We specify $X_1 = X_{QLND}$ as land, so the function is specified on a per-acre basis, consistent with much of the literature on farm production in terms of yields.

Distance from the frontier, $-\ln D^I_{it}$, is characterized as the technical inefficiency error $-u_{it}$. Equation (1b) was estimated as an error components model using maximum likelihood methods. The one-sided error term u_{it}, with a half-normal distribution, is a nonnegative random variable independently distributed with truncation at zero of the $N(m_{it},\sigma_u^2)$ distribution, where $m_{it}=\boldsymbol{R}_{it}\delta$, $\boldsymbol{R}_{it}$ is a vector of farm efficiency determinants (assumed to be the factors in the $\boldsymbol{R}$ vector), and δ is a vector of estimable parameters. The random (white noise) error component v_{it} is assumed to be independently and identically distributed, $N(0,\sigma_v^2)$. Estimated using SPF[1] techniques, technical efficiency (TE) is characterized assuming a radial contraction of inputs to the frontier (constant input composition).

Productivity impacts (marginal productive contributions, MPC) of outputs or inputs can be estimated by the first order elasticities, $MPC_m = -\varepsilon_{DI,Ym} = -\partial \ln D^I(\boldsymbol{X},\boldsymbol{Y},\boldsymbol{R})/\partial \ln Y_m = \varepsilon_{X1,Ym}$ and $MPC_k = -\varepsilon_{DI,X^*m} = -\partial \ln D^I(\boldsymbol{X},\boldsymbol{Y},\boldsymbol{R})/\partial \ln X^*_k = \varepsilon_{X1,X^*k}$. MPC_m indicates the increase in overall input use when output expands (should be positive, like a marginal cost or output elasticity measure), and MPC_k indicates the shadow value (Färe and Primont 1995) of the k^{th} input relative to X_1 (should be negative, like the slope

1 We used STATA Version 12 commands for the SPF estimation.

of an isoquant). If $\varepsilon_{X1,Rq} < 0$, increased R_q implies less input is required to produce a given output, and vice versa.

Scale economies are calculated as the combined contribution of the M outputs Y_m, or the scale elasticity SE = $-\varepsilon_{DI,Y} = -\Sigma_m \partial \ln D^I(\boldsymbol{X},\boldsymbol{Y},\boldsymbol{R})/\partial \ln Y_m = \varepsilon_{X1,Y}$. That is, the sum of the input elasticities, $\Sigma_m \partial \ln X_1/\partial \ln Y_m$, indicates the overall input-output relationship, and thus returns to scale (RTS). The extent of scale economies is thus implied by the shortfall of SE from 1; if SE<1, inputs do not increase proportionately with output levels, implying increasing RTS. We know of no other studies examining cotton farm efficiency. Previous studies on corn and on dairy farm efficiency using ARMS have found significant economies of size (Morrison et al. 2005, Tauer and Mishra 2006; Mosheim and Lovell 2009; Mayen et al. 2010).

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

Input endogeneity has been a concern in the estimation of input distance functions; if found, biased estimates result. Some studies have used instrumental variables to correct the problem, while others have argued either that (1) it was not problematic in their studies because random disturbances in production processes resulted in proportional changes in the use of all inputs (Coelli and Perelman 2000, Rodriguez-Alvarez 2007) or (2) no good instrumental variables existed, thus endogeneity was not accounted for (Fleming and Lien 2010). We estimate instruments for the 2 potential drivers of inefficiency, operator hours worked off-farm (ophours) and spouse hours worked off-farm (sphours)2.

2 For the twelve major cotton states analyzed in this study average annual operator hours worked off-farm during 2002-2014 range from 98 hours in Arizona to 620 in South Carolina and Tennessee. And, for the twelve major cotton states analyzed in this study average annual spouse hours worked off-farm during 2002-2014 range from 380 hours in California to 860 in Alabama.

The Hausman test was used to test for endogeneity. Since endogeneity was found, the predicted values for ophours and sphours are used as instruments in the SPF[3].

The Empirical Results

Stochastic frontier

The parameter estimates for cotton household model are reported in Table 3. Although most of the parameter estimates of the primal are not directly interpretable due to the flexible functional form (the elasticity measures are combinations of various parameters and data) the estimates of the acres and year dummies are directly interpretable. The acre dummy is defined as one if farms have acres operated of greater than 1000 acres and zero otherwise. The year dummy is defined as one if year is greater or equal to 2008 and zero otherwise. Hence the input model results for the acre dummy (ACREDUM), suggests a (statistically significant) decrease in productivity for farms operating at least 1000 acres. And the dummy for the year break of 2008 or later (YEARDUM) suggests a statistically significant increase in productivity in later years. Appendix Table 1 appears to support these results, indicating increases in yields over time and declines in acres operated on small, medium, and large farms. Also, the variables in the technical inefficiency effects are directly interpretable and are discussed below under farm employment.

Table 4 presents the average MPCs across all observations for each output and input to further evaluate the estimated production patterns. The MPCs for the outputs represent the proportional

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3 The problem of endogeneity occurs when the independent variable is correlated with the error term in a regression model. In the case of cotton operations, off-farm use of labor is a major source of income on many farms; for the data used off-farm income represent 5 percent of total income(earned income over earned income plus farm income)—41 percent on retirement farms, 17 percent on small farms, 7 percent on medium farms and 4 percent on large farms. For the twelve major cotton states analyzed in this study off-farm income as a proportion of total income ranges 2 percent in California and Arkansas to more than 8 percent in Alabama, and about 6 percent in South Carolina, Tennessee, and Texas. Clearly, off-farm employment by the operator or spouse may influence the impact of the labor input on output, and also the efficiency with which inputs are used.

Hence, it is desirable to use instrumental variables in order to predict operator and spousal labor off-farm from information that influences such decisions such as age and education (see Huffman et al 1997 and Huffman et al 2004 for an understanding of how instruments are used to ascertain how off-farm work decisions influence on farm labor use). More precisely, we employ instruments to predict the level of operator or spousal hours off-farm, variables that do not directly influence production but do influence the labor use off-farm. For the operator we consider population accessibility, household assets, crop production, livestock production, household wellbeing, and animal units as important drivers of off-farm employment. For the spouse we consider population accessibility, household assets, crop production, and the adjusted wage as important drivers of off-farm employment. Appendix Table 1 shows that operator hours generally held steady over time on small and medium farms, and increased slightly on large farms, while spouse hours declined on small and medium farms and increased slightly on large farms. (See USDA, National Agricultural Statistics Service and Economic Research Service Agricultural and Resource Management Survey 2014 e.g. for a definition of these variables). We include the predicated values of these two variables in the inefficiency effects reported in Table 3.

"marginal cost" or input-use share of the output. All shadow values for the output MPC's have the appropriate positive sign. Summing these MPC's yields our estimate of scale economies (Returns to scale) indicating scale economies. Since this sum is $<$ 1 inputs do not increase proportionately with output levels, implying increasing returns to scale.

The MPCs for the inputs indicate the contribution of that input to overall input use (substitutability). The largest (in absolute value) MPC is land and miscellaneous inputs on cotton farms. The *MPC*s for the outputs represent the proportional "marginal cost" or input-use share of the output. The *MPC*s for the inputs indicate the contribution of that input to overall input use (substitutability) (see Morrison et al. for a more extensive discussion of MPC's for inputs and outputs).

Appendix Table 2 reports by typology the levels of our overall performance indicators (scale economy, SE, and technical efficiency, TE) for different size farms. As shown in Appendix Table 2 the measures show strong scale economies, which are greatest for smaller farms, indicating scale inefficiency for these farms (lower unit costs associated with growth, due to increasing returns to scale). In our cotton sample technical efficiency does not increase significantly as farm size increases. However, we find that small, medium, and large sized farms significantly more efficient than retirement farms. And, as shown in Appendix Table 2 we do not find higher TE in small, medium or large farms induced by adding off-farm income compared to not working off-farm.

Comparing typologies with earned income and without we find that off-farm income boosts scale efficiency only for large cotton farms and also boosts farm and household returns for these farms (see Appendix Table 2). We find that cotton farms relying on off-farm income have significantly higher returns on household assets for medium and large sized farms. Only large cotton farms with off-farm income show an advantage in terms of returns on farm assets. It is noteworthy that on small sized farms household returns and returns on farm assets are actually smaller on farms relying on off-farm income.

Off-farm Employment

As discussed earlier, the importance of off-farm income to economic well-being of all U.S. farmers is widely acknowledged, however, it is less clear if off-farm work is actually helping farm households to improve their economic performance across farm sizes and types of enterprises. In this section we examine the drivers of off-farm hours worked off-farm by operator and spouse[4]. As noted above the variables in the technical inefficiency effects are directly interpretable. Notably we find that higher number of operator hours in off-farm work decrease technical efficiency suggesting that this activity reduces the time spent on making effective management decisions in the farm operation. In contrast we find no significant impact on technical efficiency as spouse hours (about 80 percent of the total) worked off-farm increase. Also the positive and statistically significant coefficient on year suggest that technical efficiency has increased over time.

Summary and Concluding Remarks

This study examines the economic impact of off-farm income and selected technical efficiency drivers on economic performance in key cotton-producing states. It uses an input distance 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 (Nehring and Fernandez 2005, 2007) we expect the SPF analysis to reveal that the economic impact of off-farm work is likely to vary considerably across the subset of cotton farms considered over the 2002-2014 period, and, in general, boosting the scale efficiency of smaller-scale operations. In our cotton study however, we find that off-farm income significantly boosts scale efficiency of larger farms.

4 The instrumental variable results indicate that for operator hours, household assets (-) and household wellbeing (+) are important drivers of off-farm employment. The time dummies indicate significant declines in 2008 and 2010. The instrumental variable results indicate that for the spouse hours, house hold assets (-) and the adjusted wage (+) are important drivers of off-farm employment. The time dummies indicate significant increases in 2005, 2008 and 2010. These results are available on request.

Based on preliminary results, we find that the economic impact of off-farm work to varies considerably across typology by size on cotton farms with limited livestock production as shown in Appendix Table 2. Most importantly, we find that off-farm income boosts scale efficiency and household and farm profitability on large cotton farms. It is noteworthy that we also find a dramatic increase in the share of production on large farms between 2002 and 2014; from about 40 percent to 60 percent (see Appendix Table 1). Remarkably, all of the increase occurred on large farms with off-farm income.

In summary, comparing typologies with earned income and without we find that off-farm income; (1) boosts scale efficiency only on large sized farms, (2) boosts household returns on medium and large sized farms, and (3) boosts return on farm assets only on large farms. In the case of the small farms typology, household returns and returns on farm assets are actually smaller on farms relying on off-farm income than on farms without off-farm income. It also noteworthy that technical efficiency appears to hold steady for cotton farms without income as farm size increases while declining somewhat as farm size increases for farms with off-farm income as farm size increases. In future research we will examine impact that regional production practices and trends have on these result.

We attribute scale efficiency results in the whole farm production frontier to the total impact of the operator and spouse working 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 both operators and spouses working off-farm and the primal measure is altered influencing the measure of scale efficiency). More precisely, we hypothesize 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, even though the relatively small component due to off-farm operator hours has a negative impact on technical efficiency. In future research we will examine the impact that operator and spousal hours worked off-farm may have on scale efficiency by region. As noted in footnotes 1 and 2 the twelve cotton states analyzed are quite heterogeneous in terms of off-farm hours worked off-farm and in terms of the proportion of earned income relative to total income.

Finally, we note that cropping patterns in the cotton states analyzed 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 3. Input Distance Function Parameter Estimates, 2002-2014 Cotton.

Variable	Parameter t-test	Variable	Parameter t-test
α [illegible]	7.071 (11.11)***	α [illegible]	-0.159 (5.26)***
α [illegible]	-0.239 (-5.15)***	α [illegible]	-0.016 (-1.28)
α [illegible]	-0.317 (-5.77)***	α [illegible]	-0.002 (-0.50)
α [illegible]	-0.052 (-2.49)**	α [illegible]	0.041 (2.31)**
β [illegible]	0.065 (2.64)**	α [illegible]	-0.004 (-0.34)
β [illegible]	0.063 (0.76)	α [illegible]	-0.002 (-0.15)
β [illegible]	0.062 (1.55)	α [illegible]	-0.112 (-2.95)**
β [illegible]	0.008 (6.45)***	α [illegible]	0.497 (20.39)***
β [illegible]	0.024 (8.65)***	δ [illegible]	-9,771 (-3.86)***
β [illegible]	0.005 (2.87)**	δ [illegible]	0.223 (1.37)
β [illegible]	-0.011 (-5.20)***	δ [illegible]	0.368 (4.06)***
β [illegible]	-0.001 (-1.13)	δ [illegible]	0.024 (0.46)
β [illegible]	-0.010 (-4.07)***	δ [illegible]	0.637 (1.10)
		δ [illegible]	0.192 (4.32)***
		δ [illegible]	0.391
		Pseudo-loglikelihood	-108,496.45
		Eff	0.877
		RTS	0.563

Notes: ***significance at the 1% level (t=2.977), **significance at the 5% level (t=2.145), and *significance at the 10% level (t=1.761). Source: USDA, National Agricultural Statistics Service and Economic Research Service Agricultural and Resource Management Surveys (2002-2014). The t-statistics are based on 9,233 observations for the sample derived from 12 states: Alabama, Arizona, Arkansas, California, Georgia, Louisiana, Mississippi, Missouri, North Carolina, South Carolina, Tennessee, and Texas. The coefficient for δ [illegible] does not have a t-distribution and is reported with a 95 percent confidence interval of 3717425 to .4088631 in STATA.

Table 4: MPC's for Outputs and Inputs and Return to Scale (t-statistics in Parentheses)

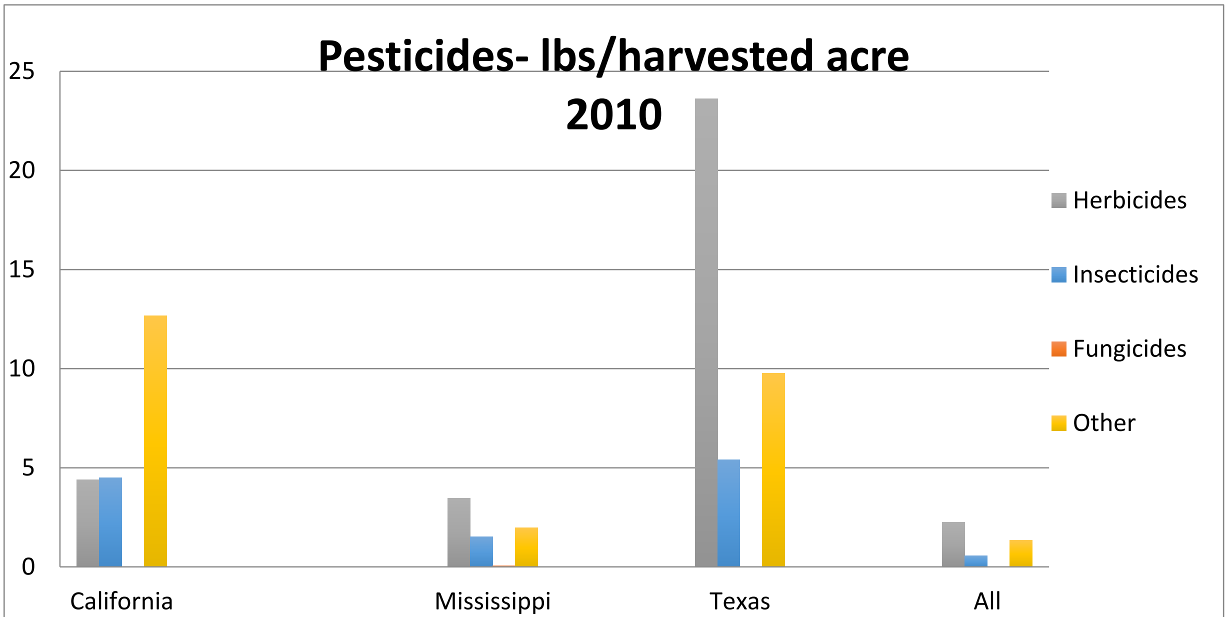
MPC_{YNCOT}	***0.001***	*(3.95)****	MPC_{XLAB}	***-0.158***	*(-3.59)****
MPC_{YCOT}	***0.558***	*(6.41)****	MPC_{XMISC}	***-0.279***	*(-27.90)****
MPC_{YOFF}	***0.003***	*(13.00)****	MPC_{XCAP}	***-0.058***	*(-5.70)****
RTS	***0.562***	*(11.09)****	MPC_{XQLND}	***-0.505***	*(-10.81)****

Notes: *** Significance at the 1% level (t=2.977). ** Significance at the 5% level (t=2.145). * Significance at the 10% level t =1.761).

Source: USDA, National Agricultural Statistics Service and Economic Research Service Agricultural and Resource Management Surveys (2002-2014).

The t-statistics are based on 9,233 observations using base weights from STATA.

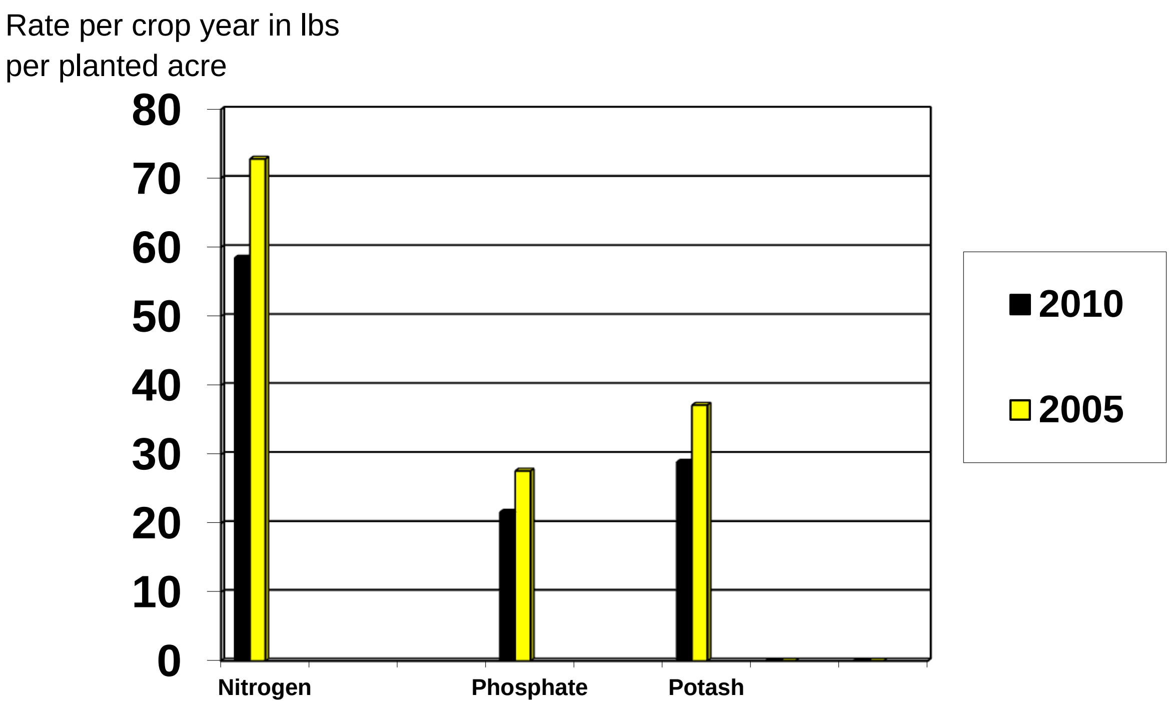
Appendix Figure 1: Pesticide use by type in selected Cotton States 2010



Selected States; Twelve major cotton states noted in Table 3.

Source; Nass QuickStats; Ag Statistics

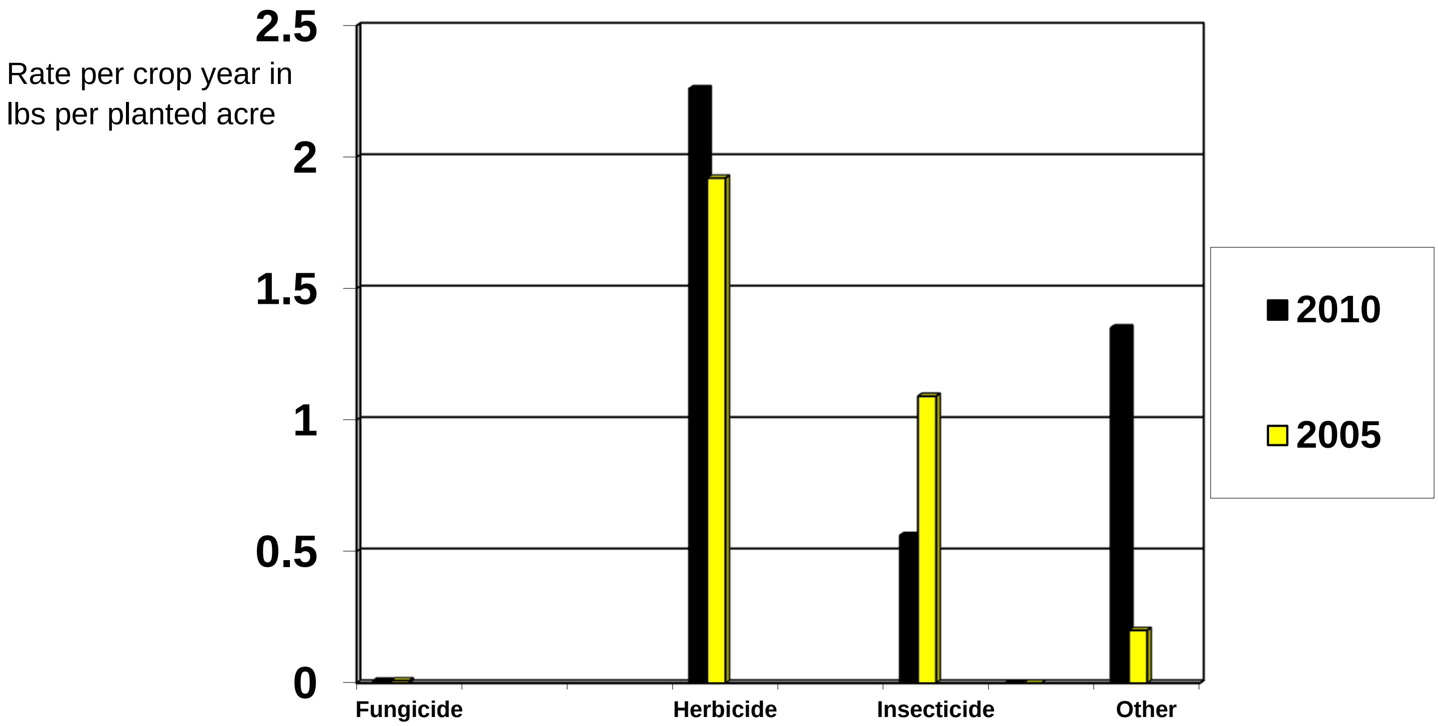
Appendix Figure 2: Fertilizer use by Cotton farmers based on Phase II data: 2010 and 2005



Selected States; Twelve major cotton states noted in Table 3

Source: NASS QuickStates and Agricultural Statistics

Appendix Figure 3**:** Pesticide use by Cotton farmers based on Phase II data: 2010 and 2005



Selected States; Twelve cotton states as noted in Table 3.

Source: NASS QuickStates and Agricultural Statistics

Appendix Table 1: Performance Measures and Technical data for Cotton farms, 2002/2008 compared to 2009/2014.

	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
Cotton Household Model									
No observations 09-14	157	236	237	511	545	530	753	207	3,276
% of Farms	12	18	12	16	14	10	14	5	100
% of Valu of Prod	1	3	4	10	9	23	38	13	100
Fert Exp per cotton acre	67	61	70	78	78	103	105	121	95
Yield	649	634	603	740	720	891	1,002	1,085	845
acresop	368	584	663	1,399	1,435	3,227	3,196	2,904	1,551
Ophours off-farm	933	0	289	0	240	0	215	0	251
Sphours off-farm	736	0	653	0	838	0	754	0	574
No observations 02-08	237	721	651	1,247	889	1,199	588	42562	5,957
% of Farms	9	25	23	16	13	7	4	4	100
% of Valu of Prod	1	7	7	16	13	25	18	12	100
Yield	596	547	580	766	766	980	973	991	784
acresop	437	664	663	1,561	1,641	3,326	3,310	2,596	1,274
Ophours off-farm	1,363	0	304	0	268	0	137	0	277
Sphours off-farm	934	0	1,005	0	1,038	0	714	0	626

Source: USDA, National Agricultural Statistics Service and Economic Research Service Agricultural and Resource Management Surveys (2002-2014).

Appendix Table 2: Characteristics of Farms Including Technical Efficiency and Returns to Scale, Cotton farms, 2002 to 2014 ARMS 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.	394	957	988	1,758	1,434	1,729	1,341	632
No. Farms	20,608	44,560	38,013	31,516	26,688	16,017	15,907	8,492
% Value of Production	1.4	5.2	5.1	13.4	11.5	24.0	26.9	12.4
Cotton Acres per Farm	133.4	273.5	280.5	707.7	640.9	1,310.4	1,250.6	941.0
Acres operated	406.1	640.2	663.4	1,500.0	1,559.7	3,278.7	3,234.9	2,727.2
Yield, lb/ac	616.6	569.0	585.3	756.8	750.7	939.7	977.5	1,027.8
pesticide/$ per *harvested cotton ac	40.91	36.40	38.19	47.76	47.98	71.00	76.32	79.03
fertilizer/$ per harvested cotton ac	78.71	66.56	77.66	87.21	86.58	115.62	111.81	131.16
Net Return on Assets	0.03	0.06	0.03	0.10	0.08	0.15	0.18**	0.10
Household returns	0.100	0.067	0.052	0.088	0.094	0.166	0.211**	0.0
Ophours	1,169	0.0	300	0.0	257	0.0	188	0.0
Sphours	845	0.0	919	0.0	959	0.0	740	0.0

Debt-Asset Ratio	0.16	0.08	0.19	0.12	0.15	0.12	0.24	0.15
Technical Efficiency	0.809	0.893	0.876	0.890	0.869	0.887	0.857	0.887
Returns to Scale	0.487	0.515	0.512	0.560	0.558	0.598	0.602**	0.587
Source: Source: USDA, National Agricultural Statistics Service and Economic Research Service Agricultural and Resource Management Surveys (2002-2014). *Note; Dollar measures are deflated using the producer prices paid index (USDA, NASS, Agricultural Prices); 2000-2002 dollars. ** indicates that for large cotton farms with off-farm income returns on farm and household assets, and the scale efficiency measure are statistically significantly higher than for large cotton farms with no off-farm income; the t-statistics are based on 9,233 observations using base weights from STATA.								