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ECONOMIC COMPARISON OF CULTURAL PRACTICES IN N.C. COTTON

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Abstract

It is frequently hypothesized that genetically modified crops can help to reduce pesticide use while maintaining or even increasing profit levels. No known studies evaluate these new technologies in the actual farm setting and no systematic empirical work has verified this hypothesis for cotton production. This study uses Data Envelopment Analysis (DEA) to assess the relative technical efficiency of pesticide use for a sample of 208 cotton producers in NC. The average technical efficiency (VRS) was only 0.36. Differences in mean efficiencies between seed type were not significant. Tobit analysis of the estimated input use efficiency showed that efficiency is significantly affected by harvest beginning and ending dates and whether stacked gene cotton is grown. Other important attributes were the use of formal plants for pest, nutrient and conservation management and whether the farmer grows herbicide tolerant cotton.

Introduction

It is frequently hypothesized that genetically modified crops can help to reduce pesticide use while maintaining or even increasing profit levels. Most of the economic studies on new cotton technologies use data from experiment station trials or on-farm tests for development of budgets. No known studies evaluate these new technologies in the actual farm setting and no systematic empirical work has verified this hypothesis for cotton production in NC.

Quantification of technical efficiencies of transgenic cotton producers and conventional producers allows studying practical improvement offered by genetically modified cotton. To analyze accurately potential productive efficiency gains of new cotton production systems compared to conventional cotton requires that we consider output and all pesticide inputs simultaneously. The use of partial productivity efficiency measures can give rise to spurious results. For example, with a simple ratio such as input per unit of output it is not easy to identify factors that influence this measure. A change in this ratio might represent either a change in the mix of other inputs or changes in output, or some combination. Furthermore, if we change the input used to judge output performance then the efficiency assessment derived can be significantly altered. Therefore, assessing productive efficiency based on partial indicators of productive efficiency, for example output per unit of herbicide input is inadequate.

The objectives of this study are twofold. The first is to assess the relative efficiency of a sample of cotton growers in North Carolina by means of Data Envelopment Analysis (DEA). DEA has a systems approach in that it takes account of the relationship between all inputs and outputs simultaneously. The efficiency results are summarized in the average and standard deviation by seed type to test for significant differences among systems of cotton production. The second objective is a Tobit analysis to consider how estimated input use efficiency is related to grower and field attributes and cotton production system.

Material and Methods

Relative Efficiency and Benchmarking

Technical efficiency is the ratio of actual production and best practice (or ‘frontier’) production. The existence of technical inefficiencies over producers offers an opportunity to reduce input without reducing outputs (input-reducing technical efficiency) or to increase output from the same amount of input (output-increasing technical efficiency). Efficiency is of particular interest when related to specific inputs that cause environmental impacts, such as pesticides. Information on the input-reducing technical efficiency of polluting inputs is useful to elucidate the possibilities of improving the environment while maintaining output levels.

Farrell (1957) introduced a simple method of measuring the efficiency of a decision-making unit directly from observed data. His approach yields a relative measure as it assesses the efficiency of a farm relative to all other farms in the sample. Farrell argued that this is more appropriate as it compares a farm's performance with the best performance actually achieved rather than with some unattainable ideal.

DEA Specification

Data envelopment analysis (DEA) is a linear programming based technique for measuring the relative efficiency of organisational units where the presence of multiple inputs and outputs makes comparisons difficult. The basic standpoint of relative efficiency, as applied in DEA, is to individually compare a set of decision-making units (farms). DEA constructs a frontier and the method simultaneously calculates the distance to that frontier for the (inefficient) farms below the frontier. The frontier is piecewise linear and is formed by enveloping the data points of the observed 'best practice' activities, that are the most efficient firms. DEA uses the distance to the frontier as a measure of efficiency. The measure provides a score for each farm from 0 (worst performance), to 1 (best performance). For a review of the DEA technique see Färe *et al.* (1994).

We used an input-oriented DEA model aiming at minimising the input level given the output level and assumed that the inputs are strongly disposable, *i.e.* the input level can be reduced at no cost. The DEA model used is described in the equation set (1a)-(1d):

$$\text{Minimise} \quad \Phi_j \tag{1a}$$

$$\text{subject to} \quad Yv_j \geq y_j \tag{1b}$$

$$Bv_j \leq b_j \Phi_j \tag{1c}$$

$$v_j \geq 0 \tag{1d}$$

where Φ_j is the measure of technical efficiency of the *j*-th farm; Y is a $p \times n$ matrix of *p* outputs produced by the *n* farms; v_j is the intensity vector of the weights attached to the *n* farms for the construction of the virtual comparison unit for farm *j*; y_j is a $p \times 1$ vector of quantities of output produced by farm *j*; B is a $m \times n$ matrix of *m* inputs used by the *n* farms, and b_j is the vector of these inputs for farm *j*.

The efficiency of the *n* farms is assessed by solving *n* LP models, in which the vectors y_j and b_j are adapted each time another farm *j* is considered. From constraint (1c) follows that Φ_j can never exceed unity. From constraint (1c); if $\Phi j < 1$, a weighted combination of other farms in the sample exists that produces at least the amount of output but with fewer inputs. This virtual reference group determines the convex combination of inputs of the efficient reference point for farm *j* and 'shows' that it is possible to reduce all the inputs of farm *j* by $(1\text{-}\Phi_j)$.

The equation set above assumes constant returns to scale (CRS). Two alternative scale properties are non-increasing returns to scale (NIRS) and variable returns to scale (VRS) which are modelled as in equation set *(1)* by adding $\Sigma v_j \leq 1$ and $\Sigma v_j = 1$, respectively. These three models are nested by inclusion in the sense that $frontier_{\text{CRS}} \supseteq frontier_{\text{NIRS}} \supseteq frontier_{\text{VRS}}$. Consequently the calculated technical efficiency (TE) figures for the CRS-specification will be highest, followed by those of the CRS-specification, which in turn will be higher than the results of the VRS specification. By comparing TE_{CRS} to TE_{NIRS}, we can determine whether production is characterized by decreasing or increasing returns to scale. If $TE_{CRS}<1$ and $TE_{CRS} = TE_{NIRS,}$ inefficiency is because of increasing returns to scale, *i.e.* the grower is producing at an inefficiently small output level. For $TE_{CRS}<1$ and $TE_{NIRS} > TE_{CRS}$ inefficiency is caused by operating at an inefficiently large output level or in the region of decreasing returns to scale.

Data

The data used in the DEA analysis were collected after the 2000 season as part of the Upland Cotton Production Practices Report survey by the USDA-NASS. A total of 275 North Carolina cotton producers were interviewed. After removing incomplete questionnaires, 208 remained for analysis. The data used are from an entire growing season. Table 1 presents summary statistics of the variables used in the analysis. As Table 1 shows, the data set consists of one output and five inputs. The inputs are aggregated measures and represent the use of herbicides, insecticides, growth regulators and defoliants in lbs. of active ingredient.

Tobit Analysis

To answer the question what type of grower is most efficient the efficiency scores for the individual farmers resulting from the DEA-analysis were further investigated in an eleven variable Tobit analysis. Field and farmer characteristics used in the Tobit analysis came from the Upland Cotton Production Practices Report survey by the USDA-NASS as mentioned above. We also used data from additional sources on weather conditions and on yield potential given the soil type.

Results

Before DEA was employed, several partial indicators of efficiency were considered to see if they yielded useful information. An input to output ratio was calculated for each of the inputs for the single measure of output (cotton lint). Sample correlation coefficients were calculated between the five partial indicators for all farms to see if the various ratios provide consistent and meaningful information. As Table 2 shows, the sample correlation coefficients vary significantly. The implication of this is that the different partial indicators will yield significantly different results with regard to farm level performance and will provide inconsistent information for benchmarking, as suggested above.

In the DEA application, the CRS, NIRS and VRS model specifications were estimated for the 208 observations. Our efficiency results are given in Table 3. On average the cotton growers in our sample had a low technical efficiency for pesticide use ranging from 0.28 to 0.36 depending on the scale assumption. The associated standard deviations were considerable (0.21 to 0.26). The individual efficiency scores showed that few farmers are operating at or near full efficiency. Full efficiency, i.e. an efficiency coefficient of 1.0 implies that no other cotton grower producer was more efficient in producing a given output level using the same set of pesticide inputs (measured in a.i.). For the VRS specification only 15 farmers were fully efficient[1]. A total of 26 farmers had an efficiency of 75 % or higher and six farmers had an efficiency of 10% or less[2].

Next, the efficiency scores were compared by seed type: Genetically modified herbicide tolerant cotton (BXN and Roundup Ready cotton), genetically modified Bt cotton for insect tolerance, stacked gene cotton (both genetically-modified insect and herbicide tolerant) and conventional cotton Based on a simple two-sided t-test for group means assuming equal variance, we could not reject the null-hypothesis that the mean scores are equal by seed type (Table 4). The highest t-statistics were found for the comparison of Bt cotton and herbicide tolerant and for Bt cotton and stacked gene cotton.

Particularly the comparison of the efficiency scores for conventional cotton with stacked gene cotton resulted in low t-statistics (Table 4), which was surprising given the difference in the average scores (Table 3). To gain more insight in this result we applied an F-test to test for significant differences in the variance of the efficiency scores between seed type (see Table 3). The results are reported in Table 5. As can be seen in this table, significant differences were found for stacked gene cotton and conventional cotton. This implies that the variance in technical efficiency of pesticide use among growers of stacked gene cotton is significantly higher than that of conventional growers and this explains the low t-statistic mentioned above.

The results for the different model specification (NIRS, CRS and VRS) provide useful information for identifying if there is an efficient size (lint yield level and input mix) in our sample to be operating at. The average results for the NIRS, CRS and VRS specification in Table 3 show that both increasing and decreasing scale inefficiencies are observed in the sample. Inspection of the individual results showed that of the total sample of 208 farmers, a majority of 139 farmers exhibited increasing return scale. This means that many growers could produce more cotton then they currently are given their input mix. In our sample, 62 growers exhibited decreasing returns to scale. This category of farmers tended to have high lint yield levels, which would be expected based on agronomic insights. On average the lint yield of these producers was 954 lbs. per acre (standard deviation 87 lbs. per acre), whereas the sample average was 796 lbs. per acre (standard deviation 146 lbs. per acre). Only seven producers were scale efficient[3], i.e. $\Phi j_{CRS}=\Phi j_{NIRS}=\Phi j_{VRS}=1$. The average yield level of these scale efficient growers was 821 lbs. of lint per acre.

Results of estimation of a double limited Tobit model of the efficiency scores (VRS specification) for 181 observations are reported in Table 6. The estimated parameters indicate that growing of stacked gene cotton was significant at the 5% level, indicating that the efficiency of this group of growers was higher compared to the reference (conventional cotton). Pesticide use efficiency is also significantly affected by harvest beginning and ending dates. Growing of herbicide tolerant cotton was nearly significant at the 5% level (P=0.052). Another important attribute is the use of formal plants for pest, nutrient and conservation management (P=0.0855).

Discussions and Conclusions

This paper focused on the heterogeneity in pesticide use efficiency among cultural practices in cotton production. High quality survey data for a sample of NC growers were used to estimate non-parametric measures of the technical efficiency with which these farmers utilize these inputs. Substantial heterogeneity was found in technical efficiency. The average technical efficiency (VRS) was only 0.36. Differences in mean efficiencies between seed type were not significant. Tobit analysis of the estimated input use efficiency however showed that growing of stacked gene cotton significantly affected pesticide use efficiency. Also significant was timing of harvesting. Other important attributes were the use of formal plants for pest, nutrient and conservation management and whether the farmer grows herbicide tolerant cotton.

Notes

1. Of the 15 VRS-efficient farmers, twelve used stacked gene cotton sees and three used conventional cottonseed. Six farmers had a VRS-efficiency of 10 % or less.
2. Of these six farmers, four used conventional cottonseed and the other two used herbicide tolerant and stacked gene cottonseed, respectively.
3. These peer farms could be used for benchmarking, assuming that their performance is consistent over the years. To test for this consistency would require further work that the data at our disposal did not facilitate.

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Table 1. Variables and average values for the sample data of 208 NC cotton producers, 2000.

Variable		Units per acre	Mean	Stand. dev.	Min.	Max.
Output:	**Lint yield**	**Lbs.**	**796.57**	**145.77**	**400**	**1200**
Inputs:	Insecticides	Lbs. of a.i.	0.5050	0.3741	0	1.7124
	Herbicides	Lbs. of a.i.	2.0859	1.5035	0	7.9633
	Fungicides	Lbs. of a.i.	0.0450	0.1925	0	1.3125
	Growth reg.	Lbs. of a.i.	1.7106	1.8643	0	7.2287
	Defoliants	Lbs. of a.i.	0.4796	0.4796	0	2.8744

Table 2. Correlation coefficients of input/output ratios

	Insect. /yield	Herb./yield	Fung./yield	Grwth reg./yield	Defol./yield
Insect./yield	1				
Herb./yield	-0.040	1			
Fung./yield	0.161	-0.053	1		
Grwth.reg./yield	0.021	0.226	0.000	1	
Defol./yield	0.210	-0.130	0.142	0.045	1

Table 3.Technical efficiency of pesticide use by seed type for three model specifications.

		By seed type			
Model specification	**Whole sample N = 208**	**Herbicide tolerant cotton (n = 74)**	**BtCotton (n = 6)**	**Stacked (n = 81)**	**Conventional (n = 47)**
CRS: Mean	0.28	0.27	0.28	0.35	0.20
St dev.	0.21	0.19	0.15	0.25	0.12
Min.	0.05	0.08	0.15	0.07	0.05
Max.	1.00	1.00	0.52	1.00	0.53
NIRS: Mean	0.32	0.29	0.36	0.40	0.24
St. dev.	0.25	0.21	0.26	0.30	0.17
Min.	0.05	0.08	0.16	0.07	0.05
Max.	1.00	1.00	0.82	1.00	0.76
VRS: Mean	0.36	0.34	0.39	0.44	0.27
St. dev.	0.26	0.24	0.25	0.30	0.18
Min.	0.08	0.08	0.19	0.10	0.08
Max.	1.00	1.00	0.82	1.00	0.76

Table 4. Results of t-test for pair wise comparison of mean efficiencies by seed types.

Comparison of:		With								
		Herbicide tolerant (n=74)			Bt cotton (n=6)			Stacked (n=81)		
		CRS	NIRS	VRS	CRS	NIRS	VRS	CRS	NIRS	VRS
BtCotton:	CRS	0.497								
	NIRS		0.888							
	VRS			0.629						
Critical value 5 %			2.000							
Stacked:	CRS	0.016			0.759					
	NIRS		0.035			0.533				
	VRS			0.032			0.720			
Critical value 5 %			1.96			1.992				
Conventional:	CRS	0.172			0.162			0.001		
	NIRS		0.040			0.174			0.000	
	VRS			0.095			0.164			0.001
Critical value 5 %			1.999			2.015			1.96	

Table 5. Results of F-test for pair wise comparison of variances of efficiencies by seed types.

Comparison of:		with								
		Herbicide tolerant ctton (n=74)			Bt cotton (n=6)			Stacked (n=81)		
		CRS	NIRS	VRS	CRS	NIRS	VRS	CRS	NIRS	VRS
Bt cotton:	CRS	1.289								
	NIRS		1.215							
	VRS			1.043						
Stacked :	CRS	1.345			1.735					
	NIRS		1.375			1.131				
	VRS			1.241			1.189			
Convent.:	CRS	1.550			1.2024			2.086*		
	NIRS		1.259			1.530			1.731*	
	VRS			1.322			1.379			1.641*

* Significant at P=0.05

Table 6. Double limit Tobit model estimates

Variable	Estimate	P-value
Intercept	1.90881	0.8275
Realistic Yield Expectation in lbs lint per acre [a]	0.00019	0.7081
Rainfall in fall (Sept 1-Nov 15) [b]	-0.02212	0.2556
Number of acres in cotton	0.00001598	0.9951
Rotation intensity	0.01240	0.5749
Years of experience growing cotton	-0.0015653	0.7234
Farmer used herbicide tolerant cotton seed	0.25593	0.0520
Farmer used Bt cotton seed	0.33585	0.2277
Farmer used stacked gene cotton seed	0.48782*	0.0002
"Farmer used formal plans for pest, nutrient and conservation management" [c]	-0.07708	0.0855
"Crops planted on specific field in 1997, '98 and '99" [c]	0.03125	0.5451
"Harvest beginning and ending dates" [c]	-0.10822*	0.0446
Log-likelihood	-193.1907828	
Degrees of freedom	169	

[a] Taken from http://www.soil.ncsu.edu/nmp/RYE_Alpha.PDF

[b] Assessed from the weather station near the field or a weighted (by distance) average of the data from the three closest weather stations.

[c] Artificial variable assessed by factor analysis of the 89 field characteristics in the Upland Cotton Production Practices Report survey by the USDA-NASS.

* Significant at P=0.05.