Technical Inefficiency and Its Determinants in the US Wheat Production

Diwash Neupane
Graduate Student, Food and Resource Economics, University of Florida
dneupane@ufl.edu

Charles B Moss
Professor, Food and Resource Economics, University of Florida
cbmoss@ufl.edu

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Diwash Neupane And Charles B Moss, University of Florida

Abstract

This paper investigates technical inefficiency in four of the major wheat-producing states in the US. The findings show that the inefficiency of wheat production varied widely in these states and has a mean value of 16 percent. Increase moisture level has positive impact on the mean efficiency while wheat's share acreage has negative impact on efficiency.

Introduction

Wheat is one of the most important crops in the United States. Wheat ranks third behind corn and soybean in terms of total value of production and acreage (Vocke and Ali, 2013). However, issues such as biofuel policy has resulted in shift of crop land areas (Rosegrant, 2008). More recently, wheat's share acreage has dropped significantly in some of the states such as Kansas and North Dakota (Vocke and Ali, 2013). Vocke and Ali (2013) find that the overall yield of wheat bushels per acre were lower than expected yield, whereas average production costs were higher in five different wheat growing Plain regions in the US. Although bad weather has resulted in wheat yield drop in some regions, numerous studies have found inefficiency in crop production[1].

Measurement of technical inefficiency provides information on whether or not a firm is producing maximum output using minimum quantity of inputs. Technical efficiency in wheat production has been estimated for different farms in different countries (Bravo-Ureta et. al.,

[1] See Bravo-Ureta et. al.(2007) for complete review

2007). However, no study has estimated technical inefficiency in wheat production in the US. Therefore, this paper examines technical inefficiency in wheat production in four major wheat-producing states. The main purpose of this study is to measure the inefficiency in wheat production in those selected states. This study also estimates the impact of drought and wheat's share acreage on technical inefficiency and analyzes the marginal effects of determinants of technical inefficiency.

Methodology and Data

This study uses stochastic frontier model to estimate wheat yield and measure technical inefficiency in the production. Different forms of the model have been formulated to measure inefficiency in the production since Aigner et. al., (1977) and Meeusen and Broeck (1977) published stochastic frontier models. This study follows the stochastic frontier model presented by Kumbhakar and Sun (2013), which uses Jondrow et. al. (1982) formula to estimate the marginal effects of exogenous variables on the inefficiency. This model allows exogenous variables to interact with both the mean and the variance of inefficiency along with the variance of the random error term. Such stochastic frontier is specified as:

$$y_{it} = \beta' x_{it} + v_{it} - u_{it} \tag{1.1}$$

where,

$$v_{it} \sim N(0, \sigma^2_{vit}) \tag{1.2}$$

$$u_{it} \sim N^+(\mu_{it}, \sigma^2_{uit}) \tag{1.3}$$

where, y_{it} is the wheat yield for each individual state *i* at time *t*. x represents inputs allocation (nitrogen and phosphorus), β's are input parameters to be estimated, v_{it} is the random noise term which is normally distributed with zero mean and variance σ^2_{vit} and u_{it} is the technical inefficiency which is non-negative and has truncated normal distribution with mean μ_{it} and variance σ^2_{uit}. Also $\varepsilon_i = v_i - u_i$, which is a composed error term. Following Jondrow et. al. (1982), $\tilde{\mu}_i = (\mu_i\sigma^2_{vi} - \varepsilon_i\sigma^2_{vi}) / \sigma^2_i$ and $\sigma_{*i} = \sigma_{ui}\sigma_{vi} / \sigma_{\mathrm{i}}$, where $\sigma^2_i = \sigma^2_{vi} + \sigma^2_{ui}$. Then u_i can be estimated by conditional mean as:

$$E(u_i / \varepsilon_i) = \tilde{\mu}_i + \sigma_{*i} \frac{\phi(\tilde{\mu}i / \sigma_{*i})}{\Phi(\tilde{\mu}i / \sigma_{*i})} \tag{1.4}$$

where ϕ and Φ represents standard normal density and cumulative distribution function respectively.

As discussed earlier, exogenous variable are allowed to interact with the mean and the variance of inefficiency term and the variance of the random noise and can be expressed as:

$$\mu_{it} = \alpha_0 + \delta'\mathrm{z}_{\mathrm{it}} \tag{1.5}$$

$$\sigma_{uit} = \exp(\alpha_1 + \gamma'\mathrm{z}_{\mathrm{it}}) \tag{1.6}$$

$$\sigma_{vit} = \exp(\alpha_2 + \lambda'\mathrm{z}_{\mathrm{it}}) \tag{1.7}$$

where, z represents exogenous variable that affects the technical inefficiency (drought representing risk factors and the wheat's share acreages) and δ, γ, λ and α's are parameters to be estimated.

Equations (1.1), (1.5), (1.6) and (1.7) are estimated using maximum likelihood methods. Finally, we estimate marginal effect of exogenous variable as $\partial E(\mathrm{u_i} \mid \varepsilon_{\mathrm{i}}) / \partial z_{ki}$[2] where $k = 1,.,3$ for each exogenous variable.

To empirically estimate the model, we use logarithmic value of yield as an output and logarithmic value of nitrogen and phosphorus as inputs. We also control states effect using state

[2] See Kumbhakar and Sun (2013)

dummy variables. Similarly, we use palmar drought severity index and wheat's share acreage as our exogenous variable.

Data

This study uses survey data from USDA/NASS/ERS. USDA/NASS provides state level data for the major Hard Red Winter wheat producing states (Kansas, Nebraska, Oklahoma, and Texas). Data include information on planted acreages, per acre wheat yield. Nitrogen and phosphorus use data is taken from the USDA/ERS's fertilizer use data. We use data for the period 1965 through 2009. However, years with missing information were dropped. Wheat's share acreage for each state was calculated by dividing wheat acreage to the sum total of other important crops acreages in each state.

Palmer drought severity index (PDSI) data is obtained from the National Climatic Data Center/NOAA. PDSI1 is the average palmer drought severity index in each state for the months of August through January (first hollow stem appearance stage), whereas PDSI2 is the average drought index for the months of February through June. PDSI index ranges between ± 7 , where -4 and below is extremely drought conditions, and +4 and above is extremely moist conditions. Similarly, 0 refers to a normal condition.

State dummy variables were used to capture state level characteristics. Each state has 34 years of observations. Table 1 provides variables description and summary statistics.

Results and Discussion

Table 2 provides yield estimates from wheat yield model. Similarly, table 3 presents result from inefficiency estimation.

Results from wheat yield estimation suggest that nitrogen is highly significant and positive, whereas phosphorus is non-significant. Estimates for state dummy variables suggest that compared to the base state of Kansas, Nebraska is positively and significantly correlated to the wheat yield, whereas both Oklahoma and Texas are negatively and significantly correlated to the wheat yield.

Results from technical inefficiency estimation predicted inefficiency range from a minimum of 0.3 percent to a maximum of 59 percent. Mean technical inefficiency in wheat production in the US is around 16 percent. Result from table 4 shows that the magnitude of the mean technical inefficiency is different among states. Parameter estimates for the inefficiency model shows that the technical inefficiency is affected by all three exogenous variables. PDSI2 coefficient is negative, suggesting a positive effect on efficiency, whereas both PSDI1 and wheat's share acre is positive suggesting negative effect on technical efficiency. Both PDSI2 and wheat's share acre have negative and significant effect on the variance of inefficiency.

Finally, figure 1 and figure 2 reports marginal effect of PDSI1 and wheat's share along with their 95 percent confidence interval. Since marginal effect of PDSI2 on technical efficiency was very low, we did not present the figure in this paper. PDSI1 has a positive effect on the levels of the inefficiency while wheat's share marginal effect is not consistent and changes its magnitude and sign.

Conclusion

This study estimated technical inefficiency in wheat yields in four major wheat-producing states in the US. This study found inefficiency in wheat production at varying level across different states. Mean technical inefficiency of 16 percent implies that realized output could be increased by 16 percent without additional resources. Although good weather conditions during crop growth period have positive effect on efficiency, its marginal impact is non-significant. Marginal effect on inefficiency is negative when wheat's share acre is low and is positive when the wheat's share increases. This study is limited by the lack of information related to socio-economic and other technological factors that could have improve the estimation.

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Appendix:

Table1. Descriptive Statistics of Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Yield	136	30.485	6.776	16.000	49.000
Nitrogen	136	59.296	17.321	27.000	112.000
Phosphorus	136	35.490	6.047	22.600	54.000
pdsii	136	0.747	1.770	-2.494	6.763
pdsi2	136	0.562	1.906	-3.216	4.566
wshare (wheat share)	136	0.471	0.237	0.106	0.855

Table2. Yield Estimates

Parameter	Estimates	SE	t-value	p-value
Intercept	2.127	0.297	7.173	0.000
Nitrogen	0.456	0.066	6.861	0.000
Phosphorus	-0.090	0.076	-1.175	0.240
NE	0.119	0.059	2.005	0.045
OK	-0.092	0.054	-1.686	0.092
TX	-0.417	0.060	-6.899	0.000

Table 3. Inefficiency Estimates

Parameter	Estimates	SE	t-value	p-value
alpha 0	-0.258	0.157	-1.639	0.101
u/pdsi1	0.045	0.016	2.862	0.004
u/pdsi2	-0.082	0.016	-5.158	0.000
u/wshare	0.664	0.261	2.540	0.011
alpha1	-0.706	0.406	-1.740	0.082
sig_u/pdsi1	0.013	0.091	0.139	0.890
sig_u/pdsi2	-0.280	0.145	-1.937	0.053
Sig_u/wshare	-3.686	1.216	-3.032	0.002
alpha2	-2.742	0.286	-9.589	0.000
sig_v/pdsi1	-0.040	0.070	-0.576	0.565
sig_v/pdsi2	0.145	0.082	1.775	0.076
sig_v/wshare	0.851	0.397	2.144	0.032

Table 4. Inefficiency for Individual States			
	Min.	Mean	Max.
Kansas	0.003	0.141	0.409
Nebraska	0.013	0.106	0.578
Oklahoma	0.007	0.252	0.474
Texas	0.006	0.139	0.589
Overall	0.003	0.160	0.589

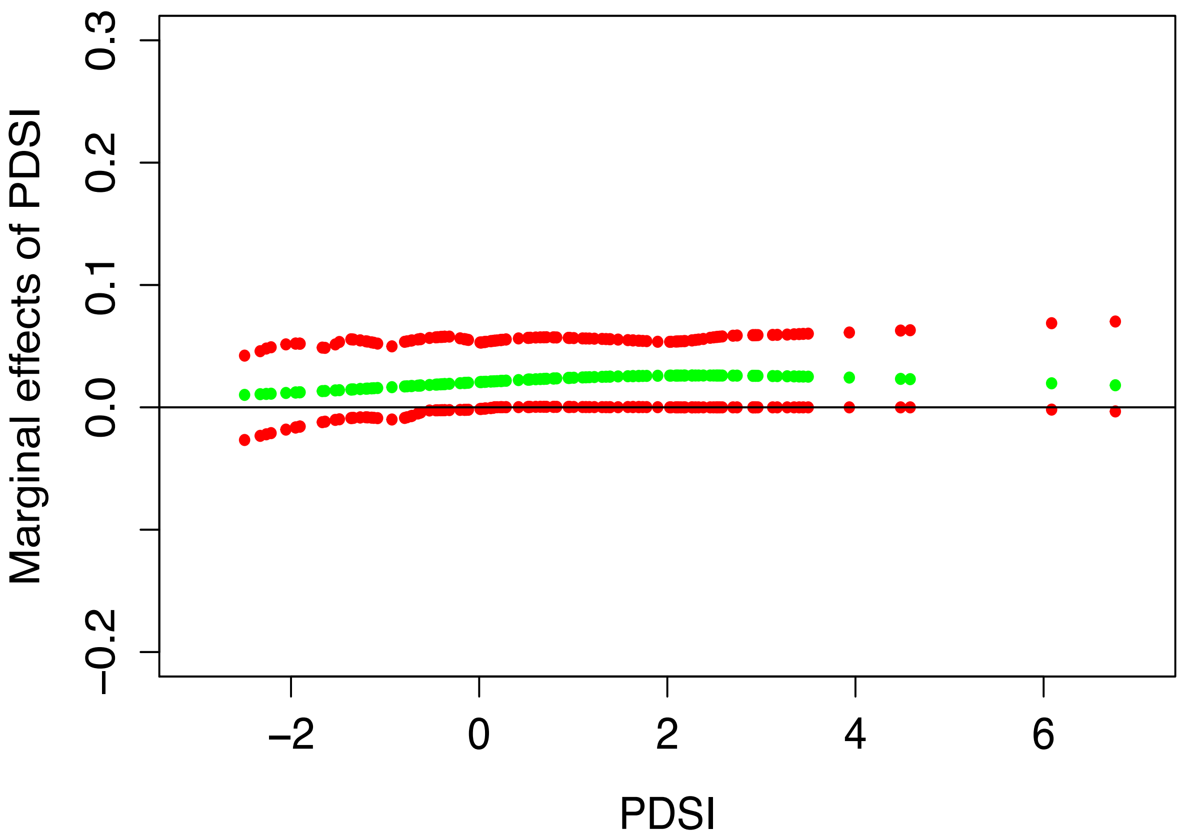

Fig 1. 95% Confidence Intervals

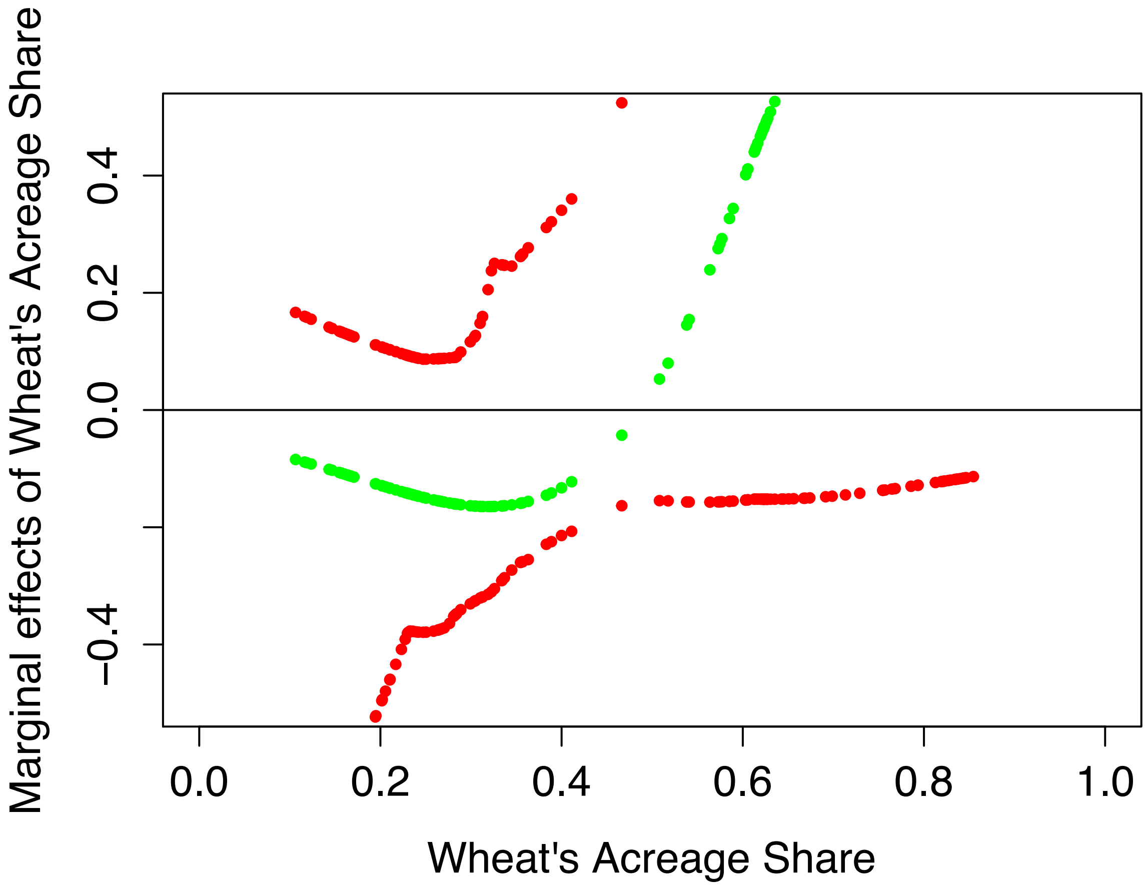

Fig 2. 95% Confidence Intervals