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An Efficiency and Productivity Analysis of the Agricultural Sector in Alabama

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Abstract: In this paper, we estimate a stochastic frontier production function to evaluate the technical efficiency of Alabama's agricultural production. The region in Alabama known as the Black Belt is a social and geographic area where the population has a high percentage of African Americans. While it is seen as a region with lower agricultural productivity and lower technical efficiency, our empirical findings show that technical efficiency in the Black Belt is not substantially different from that of the adjacent region. However, lower efficiency scores in the two regions suggest a strong potential increase in agricultural production. Among the driving forces behind technical efficiency, government payments are the leading factor that could be associated with wealth effect and capitalization of government payments, particularly in the Black Belt region.

Key words: stochastic frontier analysis, technical efficiency, agricultural production, Black Belt

JEL Classifications: C12, O47, P27

1. Introduction

Agriculture plays a crucial role in the economy and culture of the U.S. state of Alabama. According to the United States Department of Agriculture (USDA), Alabama's agricultural industry (including agribusiness) contributes the most to the state's economy. It is responsible for nearly half a million jobs and over ten billion dollars in annual earnings. In 2015, 82% of Alabama's agricultural cash receipts were from livestock and poultry, with broilers as the most valuable product, generating 60% of livestock revenue.[1]

The historical and geographical Black Belt is an important region in Alabama.[2] Along with a significant African American population and a high rate of poverty, this crescent-shaped area in the Southern U.S. is typified as an agricultural landscape with low-density settlement, poor access to education and medical care, and high unemployment. Furthermore, the origin of the Black Belt is also related to the occurrence of black soil in certain counties in this region. According to the USDA's latest annual Census of Agriculture, sales of agricultural products per county in Alabama in 2012 were 82.4 million dollars with an average of 132,875 acres of land. Corresponding values in the Black Belt were 42.3 million dollars and 167,175 acres. According to Blejwas (2007), if the Black Belt was removed from Alabama, the state would become the seventh highest in the nation in terms of agricultural productivity. This proposition is evaluated in the present study.

The usual caveats used to explain lower agricultural productivity are technical inefficiency and limited resources. Productivity is measured by comparing actual outputs with the maximum amount of outputs given inputs with the fixed technology. Efforts to maximize production are not always successful for a variety of reasons. Among these reasons, technical inefficiency is the most important and receives particular attention in the literature. With regard to unobserved technical inefficiency, Aigner, Lovell and Schmidt (1977) proposed a stochastic frontier analysis (SFA) technique by presuming non-negative technical inefficiency in the statistical noise of the traditional production function. The SFA method has since then been extensively applied in the literature in an attempt to explore producers' technical inefficiencies (Battese and Coelli, 1992 and 1995; Chambers and Quiggin, 2002; O'Donnell and Griffiths, 2006; O'Donnell, Rao and Battese, 2008; and Katuwal, Calkin and Hand, 2016). In accordance with this trend, we now apply the SFA method to explore technical inefficiency in Alabama's agricultural production.

Human capital (e.g. knowledge and experience of operators) is presumed to be the main predictor of technical inefficiency (Battese and Coelli, 1995). Empirical evidence, on the other hand, shows that scale economy stimulates output growth even in the absence of technical changes (Aly et al. 1987; Paul et al., 2004). In the Black Belt, average land per farm increased from 385 acres in 1997 to 396 acres in 2012, while, in the adjacent region, it increased from 194 acres to 203 acres. Since government payment programs affect land operated by farmers, government payment would be a factor affecting scale economy and subsequently technical efficiency. Moreover, government payment represents one of the important income sources in the Black Belt. Calhoun, Reeder, and Bagi (2000) stated that the Black Belt receives above-average Federal funds per capita. The impact of government payments on agricultural production have been studied by Sumner (2003) and Goodwin and Mishra (2006). In a departure from the existing literature, the present study treats government payment as a determinant of technical efficiency. Government payment programs are designed to maintain farmer income and would, therefore, affect potential outputs through farmers' decisions regarding conventional inputs and capitalization. Since the wealth effect of government payment depends on the original economic condition of farmers, we should distinguish wealth impact between "poor" and "rich" farmers. In our study, the former being the Black Belt and the latter is the adjacent region in Alabama.

The present paper uses the stochastic production function approach to analyze the efficiency and productivity of agricultural production in Alabama. Our focus is the agricultural productivity analysis of the Black Belt region. To the best of our knowledge, this is the first study that examines the agricultural technical efficiencies of two nearby regions that differ for economic conditions. This study could help to evaluate the impact of regional variations on technical efficiency in agricultural production and highlight implications for rural development.

The structure of the paper is as follows. In the next section, we present an overview of the stochastic frontier analysis; in section three we present the data used in our study, followed by section four that discusses the empirical model. In the last section, we provide some concluding remarks and discuss potential policy implications.

2. Theoretical Framework

Aigner, Lovell, and Schmidt (1977) developed the stochastic production frontier model and provided an empirical example using cross-sectional data. The authors assumed that the term of the production function is composed of two components: one is the Gaussian noise, due to unobserved heterogeneities of producers, and another component is producers' technical inefficiency that is assumed to be the non-negative technical inefficiency effect. This means that firm's output lies on the frontier for the most successful producers or below the frontier for those inefficient producers who use the same amount of input as the successful ones. The theoretical stochastic production frontier model is specified as:

$$Y_{it} = f(\boldsymbol{x}_{it}, \boldsymbol{\beta}_k) \exp(V_{it} - U_{it}) \tag{1}$$

where Y_{it} denotes output at the t–th observation for the i–th firm; $\boldsymbol{x}_{it}$ is an (1 x k) vector of various inputs and other explanatory variables; $\boldsymbol{\beta}_k$ is a (k x 1) vector of unknown parameters to be estimated. The random error V_{it} is assumed to be independently and identically normally distributed, i.e. $V_{it} \sim N(0, \sigma_V^2)$. As previously mentioned, the random variable U_{it} accounts for technical inefficiency in production. This requires that U_{it} follows a non-negative normal distribution and independent of V_{it}. The independent distribution between U_{it} and V_{it} allows the separation of statistical noise and technical inefficiency in the production function.

Technical efficiency is measured by the ratio of observed output to maximum possible output. We first derive the deterministic production by dropping the technical inefficiency term from equation (1) to yield:

$$Y_{it}^* = f(\boldsymbol{x}_{it}, \boldsymbol{\beta}_k) \exp(V_{it}) \tag{2}$$

where Y_{it}^* represents the maximum possible output.

The ratio between observed output (Equation 1) and maximum possible output (Equation 2) is the score of technical efficiency (TE). This is:

$$TE_{it} = \frac{Y_{it}}{Y_{it}^*} = \frac{f(\boldsymbol{x}_{it}, \beta_k) \exp(V_{it} - U_{it})}{f(\boldsymbol{x}_{it}, \beta_k) \exp(V_{it})} = \exp(-U_{it}) \tag{3}$$

When the issue of explaining technical efficiency was raised, researchers tested whether technical inefficiency depends on the observed characteristics of firms. Estimates have been obtained with a two-stage approach, which is constrained by the assumption of the relationship between normal statistic noise and the non-negative term in the production function.[3] The use of panel data can relax such a restriction in the model (Battese and Coelli, 1992; Kumbhakar and Lovell, 2000). For example, Battese and Coelli (1992) introduced the stochastic production function with time-varying technical efficiency by using panel data. They hypothesized that technical efficiency in earlier periods of the panel is a deterministic exponential function of technical efficiency in the last period of the panel. Empirical applications of SFA with a deterministic exponential function of technical efficiency include Battese and Coelli (1992), Dhehibi, et al. (2007), and Baten, Kamil and Fatama (2009). The general form of this specification can be expressed as:

$$U_{it} = (exp(-\eta(t-T))\, U_i \quad (4)$$

where T is the size of the time series component of the panel data; U_i follows the normal distribution, truncated at zero, N(μ, σ_U^2); and η is an unknown parameter to be estimated. If η is positive (negative), technical efficiency tends to improve (deteriorate) over time.

In a later study, Battese and Coelli (1995) provided a new specification of time-varying technical inefficiency and tested whether technical inefficiency depends on the observed characteristics of firms. This modeling technique has been empirically applied in Sharma and Leung (2000) and Tong and Chan (2003). In the agricultural economic context, firm-specific variables include farming experience, level of education, and farm size, among others. This can be modeled as:

$$U_{it} = \boldsymbol{z_{it}}\delta_i + W_{it} \quad (5)$$

where $\boldsymbol{z_{it}}$ is a vector of farm-specific variables. The error term, W_{it}, is a truncated normal distribution with zero mean and variance σ_U^2, which is consistent with the characteristics of U_i, as a non-negative truncation distribution.

We define the model including Equations (1) and (4) as Model A (*t–T*), and the model including Equations (1) and (5) as Model B ($\boldsymbol{z}$'s) where z is the vector of the variables in the technical inefficiency function. The corresponding empirical specifications are introduced in Section 4 of this manuscript.

3. Data Description

There are 67 counties in Alabama, 12 of which are in the Black Belt with the other 55 counties categorized as the adjacent region for the purpose of this study. The data used were primarily obtained from the USDA's Census of Agriculture, which is carried out every 5 years. Thus, production and farm-specific variables for the 67 counties were obtained 4 times across the five-year intervals, i.e., in 1997, 2002, 2007, and 2012.

As is common in the literature (e.g. Smith and Taylor, 1998, among others), the output value is treated as a proxy for the production of multi-products. For each county, agricultural output is represented by the value of agricultural products, including livestock, poultry, and crops. Conventional inputs in the data set include six categories: land, capital, livestock, labor, fertilizer, and chemicals. Land input is defined as the area of harvested cropland and all types of pastures**.** Uncultivated land and pastures are considered irrelevant to the output and are not included in the land input. Capital input is a flow construction and includes depreciation, machinery rental expenditures, and fees associated with supplies and repairs. Livestock input refers to expenses related to the purchasing or leasing of livestock and poultry each year. Labor input includes both hired and contracted labor and is measured in dollars. The inputs of fertilizer and chemicals are measured by their expenditures. Chemicals include insecticides, herbicides, fungicides, and other pesticides.

Data on farm-specific characteristics include farm size, age and race of operators, and government payments. The size of a farm operation is represented by the average land area per farm. Age refers to the average age of operators in each county. As is discussed in Huffman (1981), differences in education levels between black and white operators may lead to productivity differences on operated farms in the Southern U.S. The 1997 Census grouped operators into only two categories: white, and other races including black, thereby making the separation of black operators from others impossible. As such, the acreage ratio of farms with white operators (versus all other races) out of the total land acreage in each county is included in the inefficiency function to capture the impact of race on technical inefficiency. Government payments consist of direct cash payments received by farm operators, as defined by the Farm Bill. Government payments included in the 2012 Census of Agriculture are loan deficiency payments, disaster payments, and payments from the Conservation Reserve Program (CRP) and Wetlands Reserve Program (WRP). The CRP encourages the planting of trees on acres that have once grown soybeans and cotton. The WRP provides technical and financial assistances to landowners to protect, restore and enhance wetlands on their property.

A summary of the data is presented in Table 1. Except for *Age*, *White* (by percentage), and *Land* and *Size* (by acreage), all variables are measured in U.S. dollars and are deflated to 2009 equivalents by the implicit GDP deflator from the Federal Reserve Bank of St. Louis. We cite 2012 as an example. On average, a Black Belt county earned 40.2 million dollars with 82,098 acres of harvested cropland, with 4.56 million dollars in livestock being the major input (after capital input). The corresponding values for an adjacent average county are 87.6 million dollars of output, and 69,890 acres of harvested cropland, with 11.9 million dollars of livestock input. The average amount of government payments per county in the Black Belt was smaller than in the adjacent region (1.03 million dollars versus 1.30 million dollars). Of the four sample years, the only year the Black Belt received a higher amount of government payments than the adjacent region was in 1997. In 2012, the average age of farm operators was 60.0 in the Black Belt and 59.5 in the adjacent region. Average farm size in the Black Belt was nearly twice as large than in the adjacent region (396 versus 204 acres). The ratios of white operators (in terms of land operated) in the Black Belt and adjacent region are quite close, indicating that farms in Alabama are mainly operated by white operators, regardless of whether the farms are in the Black Belt or not.

4. Empirical Model

The Cobb-Douglas production function is applied here to represent the technology of agricultural production in Alabama. Although the Cobb-Douglas production has been traditionally applied in the literature on agriculture productivity analysis (Battese and Coelli, 1992), some more flexible production functions like the translog production function are also broadly used in the research. Unlike the nonlinear translog production function, the Cobb-Douglas function assumes constant elasticities. We believe that the constant elasticity assumption is not a severe limitation in the presence of short dynamic datasets as in our case. This argument is also supported by Hayami and Ruttan (1985). Moreover, as we include six disaggregate inputs in our model, there are fifteen interaction terms in the translog production, which would pose computational impossibilities that result in the failure of the numerical optimization convergence of the joint production and inefficiency functions. Therefore, by using the more parsimonious Cobb-Douglas specification (with output and input variables in logarithmic forms), we ensure to preserve the desired self-dual properties of the production function in a linearized version of the stochastic frontier model:

$$\log(Output_{it}) = \beta_0 + \beta_1 \log(Land_{it}) + \beta_2 \log(Capital_{it}) + \beta_3 \log(Livestock_{it}) + \beta_4 \log(Labor_{it}) + \beta_5 \log(Fertilizer_{it}) + \beta_6 \log(Chemicals_{it}) + V_{it} - U_{it} \quad (6)$$

where *Output* is the total value of product; *Land* represents the area of the harvested cropland and all types of pasture; *Capital* is the sum of depreciation, machinery rental expenditure, and supplies and repairs fees; *Livestock* represents the expenses of livestock and poultry purchased or leased each year; *Labor* includes salaries paid to hired and contracted labor; *Fertilizer* and *Chemicals* measure the expenditures of these inputs. In efficiency and productivity studies, the market value of the production factors is commonly used as a proxy for the actual amount used (see for example Bravo-Ureta, Greene and Solis (2012)). As previously mentioned, $V_{it} \sim N(0,\sigma_v^2)$ and U_{it} (non-negative normal distribution) are spherical disturbances and measure of technical inefficiencies, respectively.

We first assume that the technical inefficiency U_{it} is a deterministic exponential function of technical inefficiency in the last period of the panel. This specification is represented by Equation (4). Thus, the empirical specification of Model A is composed of Equations (6) and (4). Secondly, we assume that technical inefficiency is a function of government payment and farm-specific variables such as farm size, and operator age and race. The inefficiency function to be estimated is:

$$U_{it} = \delta_1 \log(GovP_{it}) + \delta_2 \log(Size_{it}) + \delta_3 (Age_{it}) + \delta_4 (White_{it}) + W_{it} \quad (7)$$

where *GovP* refers to government payments; *Age* is the average age of operators; *Size* denotes the size of farm operation; *White* represents the race of the main operator. Equations (6) and (7) are the empirical specification of Model B.

Models A and B are applied to the entire sample. One may be inclined to estimate the individual production function for the Black Belt and adjacent region. However, technical efficiency levels derived from different frontiers cannot compare with each other for a particular technology set that affects the individual frontier (O'Donnell, Rao, and Battese, 2008).

5. Estimation Results

We use the maximum likelihood procedure to estimate Model A (Equations 6 and 4) and Model B (Equations 6 and 7). Based on the assumptions of the distribution of V_{it} and U_{it}, the two equations of Model A (or Model B) can be estimated simultaneously by the maximum-likelihood method, which builds on the likelihood function in terms of $\sigma^2 = \sigma_V^2 + \sigma_U^2$ and $\gamma = \frac{\sigma_U^2}{\sigma^2}$ (Battese and Coelli, 1992 and 1995). In Table 2, we report parameter estimates of Model A and Model B.

We first use the values of log-likelihood function to test the specification of Models A and B. For Model A, the OLS estimation (no inefficiency) against the error components frontier is strongly rejected with a *p*–value less than 0.01 according to the log likelihood ratio (LLR) test, which follows the χ^2 distribution with degrees of freedom equal to the number of restrictions imposed. For Model B, the OLS estimation is also firmly rejected by the LLR test, indicating the rejection of the specification without technical inefficiency. Results of these tests reflect a non-negative technical inefficiency in agricultural production Table 2, we report parameter estimates of Model A and Model B.

We first use the values of log-likelihood function to test the specification of Models A and B. For Model A, the OLS estimation (no inefficiency) against the error components frontier is strongly rejected with a last period, the variable *Time* is not significant. Thus, Model A fails to detect the pattern of technical inefficiency. For Model B, the likelihood-ratio test for significance of all coefficients in the technical inefficiency function ($\delta_1 = \delta_2 = \delta_3 = \delta_4 = 0$) is strongly rejected at the 0.01 α-level of confidence. This indicates that government payment programs and farm-specific variables are factors explaining technical inefficiency in Alabama.

5.1. Estimation of Production Function

As a first step, it is important to justify the assumption of constant return to scale of the Cobb-Douglas production function. Summation of the significant coefficients of inputs is 0.939 for Model A and 1.035 for Model B, both close to unity. This empirical result is used to judge the existence of scale economics in those two regions. As argued by Mundlak (2000), deviation of the above summation from unity can be attributed to omitted variables in the production function.

For Model A, all input variables with the exception of *Chemicals* are significant with a positive sign, indicating a positive relationship between inputs and output. In terms of magnitude, *Land* and *Labor* have smaller impacts on output than other inputs. New labor-saving technology in American agriculture may explain the weak impact of labor input on agricultural production. Noting that *Land* is composed of the cultivated cropland and all types of pastures, its weak role in production is probably related to the lower importance of crops in agricultural production. In Alabama, livestock sales (especially broilers) account for a substantial share of total sales of agricultural products. This is in accordance with the estimated coefficient of *Livestock*, the greatest coefficient among the estimates. For *Fertilizer*, the significant estimation with a high value (0.208) indicates the potential benefit through increased use of fertilizers. *Capital'*s coefficient is only greater than that of *Land*. This is unexpected, since the application of new technology is certainly related to capital input, and capital should play a significant role in agricultural production.

Although it is significant in Model A, the coefficient of *Fertilizer* is insignificant in Model B. In contrast, the *Chemicals* variable is insignificant in Model A but significant in Model B. The magnitude of *Chemicals* is, however, very small in Model B. The negative impact of chemical overuse on agricultural growth (and on the environment) has been extensively documented in the literature (Affuso, Hite and Wilson, 2015, for instance). As shown in Table 1, the average land in the Black Belt is much higher than its counterpart in the adjacent area. However, the insignificant *Land* variable could suggest the lack of correlation between land area and the output. According to our estimation of Model B, farmers' productivity seems to be more sensitive to the use of *Capital* and *Livestock* rather than *Labor*. In fact, a one-percent increase in labor and livestock leads to an output increase of 0.118% and 0.388%, respectively; however, output rises by 0.435% for a one-percent increase in livestock.

The estimated coefficients in the technical inefficiency function of Model B have good statistical power. Therefore, we mainly rely on estimation results of Model B to compare agricultural productivity and technical inefficiency of the Black Belt and adjacent regions.

5.2. Estimation of Inefficiency Function

In Model B, we hypothesize that technical efficiency depends on *GovP*, *Size*, *Age*, and *White*. For a significant coefficient, the negative (positive) sign indicates a positive (negative) relationship between the relevant variable and technical efficiency. Estimated coefficients of *GovP*, *Size*, *Age*, and *White* are all Table 2, we report parameter estimates of Model A and Model B.

We first use the values of log-likelihood function to test the specification of Models A and B. For Model A, the OLS estimation (no inefficiency) against the error components frontier is strongly rejected with a coefficient of *Size* shows a negative impact of farm size on technical efficiency. Thus, large farm size in the Black Belt may lead to lower technical efficiency. For *Age*, the positive sign provides evidence that older operators are associated with a lower technical efficiency. The small magnitude of *Age* (0.040), however, indicates that age impact may not be important.[4] The significant variable *Whit*e implies that there is an explicit relationship between race and technical efficiency. The positive sign of *Whit*e indicates that farms operated by the white operators have a lower efficiency than farms with operators in the 'black and other races' category. However, we cannot directly compare technical efficiency between farms operated by white and black operators, since African American is grouped with other races in the census data.

6. Technical Efficiency Measurement

Based on the estimation results of Model B, technical efficiency scores for the Black Belt and adjacent region are calculated using Equation 3 and summarized in Table 3. Given the assumption of using the same technology set, we can compare the efficiencies of agricultural production in different regions (O'Donnell, Rao and Battese, 2008). Between 1997 and 2012, the average annual efficiency score is 0.616 in the Black Belt, while its counterpart in the adjacent region is 0.678. This provides evidence of a lower technical efficiency in the Black Belt compared to that in the adjacent region. However, the gap is Table 2, we report parameter estimates of Model A and Model B.

We first use the values of log-likelihood function to test the specification of Models A and B. For Model A, the OLS estimation (no inefficiency) against the error components frontier is strongly rejected with a 1997, followed by a decrease in technical efficiency. The same pattern of change in technical efficiency in the two regions may justify the assumption of similar technology throughout the Alabama counties. For each sample year, the Black Belt has a lower efficiency than the adjacent area, with a gap between the two ranging from –0.053 in 2012 to –0.071 in 2002. The results of the Welch two sample t-test show that the null hypothesis of a null true difference in means is rejected for the sample year 1997 and 2007 (p-value = 0.01).

Since government payment is the most important determinant of technical efficiency, as suggested by the estimation results of the inefficiency function in Model B, we calculate the marginal effects of government payments on the scores of technical efficiency in the Black Belt and the adjacent region. The marginal effect of farm-specific variables on efficiency is estimated by taking partial derivative of $-U_i$ conditional on x_i and z_i (Katuwal, Calkin and Hand, 2016). As reported in the lower half of Table 3, on average, a one-percent increase in government payment would raise technical efficiency by 0.330% in the Black Belt and 0.307% in the adjacent region. In 1997, the marginal effect of government payments on technical efficiency is higher in the Black Belt than in the adjacent region (0.343 versus 0.267). Changes in government payments have a marginally lower efficiency in 2002 and a marginally higher efficiency in 2007 and 2012 in the Black Belt, relative to the corresponding values in the adjacent region. Based on these comparisons, we can claim that government payments generally contributed more to the Black Belt than to the adjacent region; this advantage, however, is not stable and tends to diminish across the modeled years.

7. Sources of Agricultural Growth

Finally, it is important to note the contribution of technical efficiency to agricultural production in Alabama. Thus, following the methods in Lin (1992), we evaluate how changes in technical efficiencies (and other physical inputs) between the two latest census years, 2007 and 2012, contribute to agricultural growth in the Black Belt and adjacent regions.

We restate Equation (3) in a general form:

$$TE = \frac{Y(\mathrm{t})}{f(\boldsymbol{x},\mathrm{t})} \tag{8}$$

where t is a time index.

Taking the logarithm of each side of Equation (8) and differentiating each term with respect to t yields the following equation:

$$\widehat{TE} = \hat{Y} - \sum_{i=1}^{k} \frac{\partial \log f(X,t)}{\partial X_i}\frac{\partial X_i}{\partial t} - \frac{\partial \log f(X,t)}{\partial t} \tag{9}$$

where $\widehat{TE} = \frac{\partial \; logTE}{\partial \; TE}$ and $\hat{Y} = \frac{\partial \; logY}{\partial \; Y}$.

In Equation (9), the second term on the right side represents the effect of input changes on production growth, which is approximately equal to the sum of input growth rates weighted by relevant production elasticities. The third term is the total factor productivity (TFP), which is the portion of agricultural growth not explained by inputs in the production function. Therefore, TFP captures the effects of technology changes and other unobserved factors affecting production.

By rearranging Equation (9), we obtain the following formula to decompose changes in agricultural output:

$$\hat{Y} = \widehat{TE} + TFP + \sum_{i=1}^{k} \frac{\partial \log f(X,t)}{\partial X_i} \frac{\partial X_i}{\partial t} \quad (10)$$

The decomposition of agricultural growth in the Black Belt and adjacent regions for the two last census Table 2, we report parameter estimates of Model A and Model B.

We first use the values of log-likelihood function to test the specification of Models A and B. For Model A, the OLS estimation (no inefficiency) against the error components frontier is strongly rejected with a Belt is 2.83%, higher than the 2.07% in the adjacent region. For individual inputs, livestock (i.e. cattle, hogs and broilers) is the most important input and explains a 1.71% output growth in the Black Belt. For the adjacent region, the most important input is capital, which leads to a 0.86% growth in output. While the Black Belt greatly relies on livestock to increase agricultural production, the adjacent region relies instead on capital, which may assure the long-term development of agriculture. The contribution from Table 2, we report parameter estimates of Model A and Model B.

We first use the values of log-likelihood function to test the specification of Models A and B. For Model A, the OLS estimation (no inefficiency) against the error components frontier is strongly rejected with a region. As a residual, the TFP is dependent on estimates of the other components. Moreover, the TFP may impact the production of technical changes, which we fail to capture in the model by incorporating the Hicksian neutral technology in the production function.

8. Conclusions

This study analyzed the efficiency and productivity of the agricultural sector in the State of Alabama. Stochastic Frontier Analysis was used to test potential differences in efficiency and productivity between a less economically developed region known as the Black Belt (12 counties) and the rest of the counties that are adjacent to this region (55 counties). Estimation results, based on a panel data analysis, provide evidence that there is not statistically nor economically significant difference in agricultural technical efficiency between these two regions (0.616 versus 0.678). Thus, we reject the hypothesis that lower productivity in Alabama is mainly attributed to the Black Belt. As Schultz (1964) observed, a poor region can be “poor but efficient”. The relatively lower scores of technical efficiency in the Black Belt and adjacent regions indicate that there is a strong potential for these two regions to enhance the technical efficiency of agricultural production. This is particularly important for the Black Belt since agriculture plays an important role in this region in terms of income and employment. In addition, we found that federal government payments to farmers are an important determinant of technical efficiency (stronger than farm size and operator's age and race in terms of magnitude).

Government, charity organizations, and other not-for-profit institutions have historically attempted to alleviate poverty in the Black Belt. Since agriculture is the most important economic sector of the area, a significant number of support programs are implemented in this sector. Poverty alleviation programs and other public policies should be directed towards improving the agricultural technical efficiency of the Black Belt area by encouraging the use of capital inputs and motivate young farmers to focus on agricultural education and entrepreneurship. An increase in capital investment in the Black Belt would maintain the level of potential output for the long run. In Black Belt counties, as compared to adjacent counties, government payments account for high changes in overall wealth. In terms of the ratio of government payments to agricultural revenues, the average value is 5.31% in Black Belt counties and 1.87% in adjacent counties during the four census years. The modest distortionary effects of government payment programs on production have been confirmed by Roe, Somwaru, and Diao (2003). However, with regard to technical efficiency, the distortionary effects of government payments would probably not be considered modest.

This study reveals patterns and provides new insights regarding technical efficiency in Alabama's Black Belt. The evidenced contribution of government payments to agricultural production may imply a new approach for evaluating the impact of U.S. agricultural policies on rural development. However, in addition to farm-specific variables, uncertainties related to natural disasters and lack of rainfall also affect technical efficiency in agricultural production (Chambers and Quiggin, 2002; O'Donnell and Griffiths, 2006). Including these uncertainty factors in the model specification may either increase or decrease the impact of government payments and farm-specific variables on efficiency scores. This could be a standalone study that should be pursuit in the future.

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Endnotes

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1. http://www.netstate.com/economy/al_economy.htm, accessed on 5/21/2016.

2. The list of counties included in Alabama's portion of the Black Belt varies. According to the USDA Census, it includes 12 counties: Autauga, Bullock, Dallas, Elmore, Greene, Hale, Lowndes, Macon, Marengo, Montgomery, Perry, and Sumter. This definition is applied in this paper.

3. In the first stage, the frontier production function and technical inefficiency terms are estimated. In the second stage, the method of Ordinary Least Squares (OLS) is applied to regress inefficiency scores on

explanatory variables. The specification in the second stage conflicts with the independence distribution assumption of technical inefficiency used in the first stage.

4. We also estimated the specification with the level and squared *Age* to test a nonlinearity pattern of age effect. The computational procedure failed to converge to a stable maximum value of the objective function of the LL; consequently, *Age* (level) was included in the specification.

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Table 1. Summary Statistics on Variables

	1997			2002			2007			2012		
	mean	min	max	mean	min	max	mean	min	max	mean	min	max
						The Black Belt						
Output	26160123	12731864	44902511	27499082	11031791	52008018	31001928	13808125	59413977	40170179	14463042	73601171
Land	138329	88128	212672	110682	68991	175456	88031	52962	143224	82098	37436	147304
Capital	2760697	1573227	4809019	5749168	3162658	10132696	5675817	3396552	10225615	5878076	3554694	10265842
Livestock	2291402	193567	5473727	2793212	86745	9200778	3738643	332874	13094088	4561715	245217	19639208
Labor	3176663	1108846	7122255	3760687	1587190	6182304	3623691	123287	7346867	3931628	1823919	7720529
Fertilizer	1515530	701201	2962479	1132367	618934	1865007	1549304	645201	2615736	1791049	403942	4337867
Chemicals	846590	185876	1902345	775621	143011	2044357	733557	155136	1900672	974135	303194	2396092
GovP	1167707	805035	2439462	1218330	654100	2281146	1629184	865063	5207841	1026014	591182	2486385
Size	385	202	542	381	165	536	371	164	484	396	164	603
Age	56.3	54.2	57.6	57.8	56.9	59.3	58.4	56.2	59.7	60.0	58.0	61.8
White	95.2%	91.2%	99.2%	92.6%	82.2%	99.1%	92.0%	86.6%	98.0%	91.9%	85.6%	98.9%
						The adjacent region						
Output	68843851	1842095	443801356	63586534	1727857	395578375	75702470	1727857	425648797	87608618	1952924	438827901
Land	106856	32897	226987	92946	27346	214589	78503	20401	194137	69890	16956	189890
Capital	3739123	605431	11655015	7339629	532189	24688189	8203001	904103	29653564	9010760	676722	28600078
Livestock	8437595	201259	57072902	10157909	58611	69775402	12224796	65753	94707913	11882616	216703	99232034
Labor	3130478	58968	22739684	3308672	70333	25962395	3284436	77054	23052582	3617838	173933	16153897
Fertilizer	2347049	239716	7595277	2026923	146528	7178694	2815815	224998	10526640	3775182	151122	14751029
Chemicals	1730826	20510	8525939	1521375	14067	6708632	1418340	19520	9394456	2319762	42770	12061247
GovP	817901	28202	3295774	1395052	28133	5708726	1973785	19520	8430764	1299356	37068	4814044
Size	194	85	536	202	91	523	185	86	459	204	97	419
Age	55.0	52.4	58.4	56.9	53.9	61.6	57.8	54.9	62.7	59.5	57.0	64.1
White	98.6%	92.3%	100.0%	97.8%	89.7%	100.0%	97.3%	85.8%	99.7%	96.9%	87.2%	99.9%

Note: Data source is the USDA's Census of Agriculture. All variables are expressed in dollar amounts (deflated to 2009 equivalents) except for Land and Size (in acreage), Age, and White (in percentage)

Table 2. Estimations of the Stochastic Frontier Production Function

		Model A ($T–t$)		Model B (z's)	
		Coef.	S.E.	Coef.	S.E.
Stochastic Frontier					
Intercept	β_0	3.977 [a]	0.715	4.067 [a]	0.692
Land	β_1	0.143 [b]	0.064	–0.031	0.074
Capital	β_2	0.195 [a]	0.043	0.388 [a]	0.059
Livestock	β_3	0.330 [a]	0.030	0.435 [a]	0.022
Labor	β_4	0.044 [c]	0.027	0.118 [a]	0.030
Fertilizer	β_5	0.228 [a]	0.058	–0.093	0.083
Chemicals	β_6	0.046	0.039	0.094 [c]	0.045
Time	β_7	0.020	0.024		
Inefficiency Function					
Government payments	δ_1			–1.629 [b]	0.714
Size of farm	δ_2			0.263 [b]	0.137
Age	δ_3			0.040 [b]	0.019
White	δ_4			0.877 [b]	0.436
Variance parameters					
Sigma–squared	σ^2	0.542 [a]	0.130	0.139 [a]	0.030
Gamma	γ	0.924 [a]	0.023	0.630 [a]	0.148
Log–likelihood function		–46.6		–84.0	
LLR test of the one–side error		95.3 [a]		20.5 [a]	

Note: Significant levels: a $p \leq 0.01$, b $p \leq 0.05$, and c $p \leq 0.1$.

Table 3. Technical Efficiency and Marginal Effect of Government Payment

Region	1997	2002	2007	2012	Average in 1997–2012
			Technical efficiency		
Black Belt					
Mean	0.693	0.551	0.593	0.630	0.616
Standard deviation	0.085	0.107	0.114	0.096	
Annual growth		–4.10%	1.52%	1.25%	
Adjacent region					
Mean	0.748	0.621	0.659	0.683	0.678
Standard deviation	0.142	0.127	0.129	0.136	
Annual growth		–3.38%	1.21%	0.72%	
			Marginal effect of government payment		
Black Belt	0.343	0.312	0.324	0.341	0.330
Adjacent region	0.267	0.322	0.322	0.317	0.307

Note: Authors' calculation based on the estimation results from Model B (z's) where technical efficiency is explained by farms' characteristics and government payments.

Table 4. Accounting for Agricultural Output Growth Between 2007 and 2012

	Coef.	Changes in x's	Contribution
	The Black Belt		
Output			5.91%
Land Capital	0.435	0.71%	0.31%
Livestock	0.388	4.40%	1.71%
Labor	0.118	1.70%	0.20%
Fertilizer Chemicals	0.094	6.56%	0.62%
Technical efficiency			1.25%
Residual (TFP)			1.83%
	The Adjacent Region		
Output			3.15%
Land Capital	0.435	1.97%	0.86%
Livestock	0.388	-0.56%	-0.22%
Labor	0.118	2.03%	0.24%
Fertilizer Chemicals	0.094	12.71%	1.19%
Technical efficiency			0.72%
Residual (TFP)			0.35%

Note: Authors' calculation.