Does Risk or Variability in Federal Farm Programs Affect Efficiency and Productivity?

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Abstract

This paper evaluates the importance of short-run and long-run risk or variability in direct government payments (commodity programs and conservation) and crop insurance on efficiency and productivity. First, the primal production function is estimated using double-heterogeneity stochastic frontier analysis with decomposed pure random error (v) and one-side error (u) that is linked to productivity and technical efficiency, respectively. Second, two sets of alternative panel estimator of double-heterogeneity stochastic frontier model is presented using pure random error (v) and one-side error (u) independently to transform variables. An empirical application to 48 U.S. states for the period 1960 to 2004 suggests differences in parameter coefficients of the production function and double-heterogeneity function. In addition, the difference in the panel parameter coefficient is due to the use of pure random error (v) and one-side error (u) to transform variables.

Keywords: *Direct government payments; crop insurance programs, efficiency and productivity; alternative panel estimators; stochastic frontier analysis; U.S. State-level data, 1960 to 2004.*

JEL Classification Numbers: *Q18, C33, Q24.*

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1 Introduction

During the recent sequestration discussions, including discussions of current federal farm programs, policy makers, commodity groups and producers voiced opinions about the differential implications on agriculture sector. In particular, the sequestration discussion revolved around the crop insurance program (CIP) or Title XI and direct government payments (DGP) that include the commodity program or Title I and conservation or Title II. Even though Supplemental Nutrition Assistance Program forms and plays a major role in the federal farm programs and economic growth, it is not part of the analysis as it is related to consumption rather than production of agriculture. The effects of federal farm programs including DGP and CIP on the structure of the U.S. agriculture has long been an economic as well as political concern. Literature has examined the causes and effects of DGP and CIP on specific policy aspects of the U.S. farm structure. For example, earlier research looked at the impact of DGP and CIP on farm real estate, changes in the input demand functions or output supply functions apart from asymmetric issues. These issues were evaluated using regional and farm data for individual crops or farm production systems. Others looked at the impact of CIP and DGP on efficiency measures by endogenizing these programs into the production function. Further, most of the earlier research looked at the sources and causes without much emphasis on the risk or variability in CIP and DGP.

This research bridges this gap by evaluating the importance of short-run and long-run risk or variability in DGP and CIP on efficiency and productivity measures of the U.S. agriculture sector[1]. This is accomplished by linking the pure random error (v) and one-side error (u) of stochastic frontier analysis (SFA) model to productivity and efficiency, respectively, based on primal production theory.

1.1 Need for Evaluating Risk or Variability in DGP and CIP

The importance and reliance of DGP and CIP as risk management tools in agriculture production is on the rise due to increased production, marketing, financial and policy risks faced by the producers' in the global economy. Further, variability in DGP and CIP due to changes initiated by the farm bill every five years also contributes to producers' decisions to invest in new technologies as well as their risk perceptions. For example, due to the introduction of new farm programs in 2008, there has been changes in the acreage of different commodities in certain U.S. production regions. In addition, changes in DGP and CIP affects producers' decisions to determine a priori how much to invest, allocate and utilize input resources efficiently leading to productivity growth or decline. Further, due to the increased importance of DGP and CIP to the U.S. agriculture sector, the ability to quantify changes in DGP and CIP risk or variability in the short- and long-run could help not only producers, but also, policy makers.

< Insert Figures 1 and 2 >

[1]What is efficiency? The efficiency concept introduced by Farrell (1957) is the ratio of the observed output to realized output, i.e., output that could be produced if it were 100 percent efficient from a given set of inputs. Following Griliches (1996), productivity defined as a residual concept, is the ratio of aggregate output quantity index over aggregate input quantity index.

Figure 1 shows state level trends in DGP short- and long-run risk or variability from 1960 to 2004. The rolling window standard deviation of real DGP and CIP for the last 5 years represents the short-run risk or variability. Similarly, Figure 2 shows state level trends in CIP short- and long-run risk or variability. In contrast, the cumulative standard deviation of real DGP and CIP starting with 5 years and cumulating over 45 years represents the long-run risk or variability. Figures 1 and 2 show the short- and long-run variability in DGP and CIP is positive and varies widely across individual states over the analyzed period. Evaluating the importance of short- and long-run variability in DGP and CIP across 48 U.S. states over 45 years could help in understanding how these changes influence domestic agricultural production efficiency and productivity.

This research has two-fold contribution. First, the error of stochastic frontier analysis (SFA) model decomposed into pure random error (v) and one-side error (u) is linked to productivity and efficiency, respectively, based on primal production theory. Specifically, the importance of short- and long-run variability in CIP and DGP on efficiency and productivity is examined. Second, panel statistical procedures, including, Wallace-Hussain (WH), Amemiya (AM) and Swamy-Arora (SA) approaches forms basis for the alternative two-way random effects panel SFA estimators proposed in this research. In section two, details of the double-heterogeneity SFA model along with alternative two-way random effects panel SFA estimators are presented. Section three provides details of the output quantity index, the input quantity index and construction of the implicit DGP and CIP quantity index used in the analysis. An application to 48 U.S. states from

1960 to 2004 along with the results of alternative two-way random effects panel SFA estimators are presented in the fourth section.

2 Double Heterogeneity SFA Production Function Model for Inefficiency and Productivity

Primal production theory assumes that the relationship between nonallocable exogenous input vector ($\mathbf{x}$) used in the production of an endogenous aggregate output (y) is represented as

$$y = f(\mathbf{x}; \beta) \tag{1}$$

The primal production function can be estimated using SFA[2] that decomposes the traditional error (ϵ) into a symmetrical random error (v) and a one-sided error or inefficiency (u). The stochastic frontier model for primal production function is represented as

$$y = f(\mathbf{x}; \beta) + v - u \tag{2}$$

where y represents endogenous dependent variable and $\mathbf{x}$ is a vector of exogenous independent inputs including time used in the production function; β is a vector of coefficients associated with inputs; and traditional random error (ϵ) is decom-

[2] SFA was introduced in 1977 by Aigner Lovell and Schmidt (normal-half normal and an exponential distribution), Meeusen and van den Brubeck (exponential distribution), and Bates and Corra simultaneously that decomposes the error term (ϵ) into a symmetrical random error (v) and a one-sided error or inefficiency (u)

posed into pure random error (v) and negatively skewed one-sided inefficiency (u) represented by alternative distributions including half normal, exponential, or truncated normal.

Since its introduction in 1977, SFA has been evolving theoretically with a surge in empirical application. The last decade saw the introduction of fixed-effects and random parameters SFA panel models and time invariant and time variant models. These advancements corrected for heteroskedasticity/heterogeneity and alternative distributions (half normal, exponential, or truncated normal distribution) of technical efficiency term (u). Additionally, research has investigated the influence of a broader set of determinants of technical efficiency, namely geographic variables, market structure conduct and performance hypothesis, policy variables and size of the firm on inefficiency. Equation (2) can be extended by introducing double heterogeneity in the random error (v) and the one-sided inefficiency (u) as

$$\begin{aligned} y &= f\left(\mathbf{x};\beta\right) + v - u \\ \sigma_{\mathrm{u}}^2 &= \exp\left(\delta'\mathrm{z}\right) \\ \sigma_{\mathrm{v}}^2 &= \exp\left(\delta'\mathrm{z}\right) \end{aligned} \tag{3}$$

where σ_{u}^2 is the variance in the inefficiency term, σ_{v}^2 is the variance in the random error. The variances in the inefficiency and random error terms is modeled as a function of risk or variation in z variables including short-run and long-run DGP and CIP risk or variability. The inefficiency and random error variances in equation (3) can be paraphrased as variance in inefficiency and variance in productivity or TFP measures.

2.1 Linking Random Error, v to Productivity

The production function assuming inefficiency is defined as

$$\begin{aligned} y &= f(\mathbf{x}; \beta) + v - u \\ &= f(\tilde{\mathbf{x}}; \beta) + v \end{aligned} \tag{4}$$

where $f(\tilde{\mathbf{x}}; \beta)$ is equal to $f(\mathbf{x}; \beta) - u$.

Following Griliches (1996), productivity defined as a residual concept, is the ratio of aggregate output over inputs. This concept of productivity is incorporated into the stochastic frontier production function with decomposed error terms, $y = f(\mathbf{x}; \beta) + v - u$, where v constitutes a conventional random error or productivity and u constitutes one-side disturbance (with three alternative distributions - half normal, exponential, or truncated normal distributed) which represents inefficiency. Equation (4) is rewritten to define productivity as

$$TFP = v = \frac{y}{f(\tilde{\mathbf{x}}; \beta)} \tag{5}$$

The stochastic frontier production function with double heterogeneity defined in equation (3) and productivity liked to random error (v) defined equation (5) is used to examine the importance of short- and long-run risk or variability in DGP and CIP on inefficiency and productivity. The model is represented as

$$\begin{array}{lcll} y & = & f(\mathbf{x};\beta)+v-u & Output \\ \sigma^2_{\text{inefficiency}} & = & \exp(\delta' \text{z}) & Inefficiency \\ \sigma^2_{\text{productivity}} & = & \exp(\delta' \text{z}) & Productivity \end{array} \tag{6}$$

where z include the short- and long-run risk or variability in DGP and CIP. These z variables helps to understand the importance of DGP and CIP variability on inefficiency and productivity.

Next, alternative panel estimators of double heterogeneity stochastic frontier production function are presented. These estimators are built on Wallace-Hussain (WH), Amemiya (AM) and Swamy-Arora (SA) approaches and use *random residuals (v)* estimated from pooled SFA, within SFA, between cross-section SFA and between time-series SFA models. A second set of alternative panel estimators of double heterogeneity stochastic frontier production function are also presented. These estimators use *one-sided efficiency (u)* estimated from pooled SFA, within SFA, between cross-section SFA and between time-series SFA models.

2.2 Wallace-Husain and Amemiya Two-way Panel Estimators of Stochastic Frontier Production Function

With panel data, the stochastic frontier production function with heterogeneity in the random error (v_{it}) and the one-sided inefficiency (u_{it}) is represented as

$$\begin{aligned} y_{it} &= f\left(\mathbf{x}_{it};\beta\right) - u_{it} + v_{it} \\ \sigma^2_{u,it} &= \exp\left(\delta' \mathrm{z}_{it}\right) \\ \sigma^2_{v,it} &= \exp\left(\delta' \mathrm{z}_{it}\right) \end{aligned} \tag{7}$$

where $i = 1, ..., I$ and $t = 1, ..., T$ represents cross-sectional and time-series dimensions.

To estimate the WH and AM two-way random effects[3] stochastic frontier production function with heterogeneity, equation (7) needs to be transformed as

$$\begin{aligned} y^*_{it} &= f\left(\mathbf{x}^*_{it};\beta\right) - u_{it} + v_{it} \\ \sigma^2_{\mathrm{u,it}} &= \exp\left(\delta' \mathrm{z}^*_{it}\right) \\ \sigma^2_{\mathrm{v,it}} &= \exp\left(\delta' \mathrm{z}^*_{it}\right) \end{aligned} \tag{8}$$

where $y^*_{it} = \Omega^{-1/2} y_{it}$ or $y^*_{it} = y_{it} - \theta_1 y_{i.} - \theta_2 y_{.\,t} + \theta_3 y_{..}$ with $y_{i.}$, $y_{.\,t}$ and $y_{..}$

[3] The additive errors of the two-way error components structure is represented in vector form for normal random error, $v_{it} = W_\mu \mu_i + W_\lambda \lambda_t + W_\varepsilon \varepsilon_{it}$ and one-sided error, $u_{it} = W_\mu \mu_i + W_\lambda \lambda_t + W_\varepsilon \varepsilon_{it}$ where $\begin{array}{l} W_\mu = (I_I \otimes \iota_T)\,;\ \mu' = (\mu_1, ..., \mu_I) \\ W_\lambda = (I_T \otimes \iota_I)\,;\ \lambda' = (\lambda_1, ..., \lambda_T) \\ W_\varepsilon = (I_I \otimes I_T)\,;\ \varepsilon' = (\varepsilon_{11}, ..., \varepsilon_{IT}) \end{array}$ and represent the random error components with zero mean and covariance matrix $E\begin{pmatrix} \mu \\ \lambda \\ \varepsilon \end{pmatrix}(\mu' \lambda' \varepsilon') = \begin{pmatrix} \sigma^2_\mu I_N & 0 & 0 \\ 0 & \sigma^2_\lambda I_T & 0 \\ 0 & 0 & \sigma^2_\varepsilon I_{NT} \end{pmatrix}$.

in the above equation represents the cross-section, time-series, and the overall mean of the variable and computed as $y_{i.} = \sum_{t=1}^{T} y_{it}/T$, $y_{.t} = \sum_{n=1}^{N} y_{it}/I$ and $y_{..} = \sum_{n=1}^{N} \sum_{t=1}^{T} y_{it}/IT$, respectively. The omega is defined as

$$\Omega^{-1/2} \equiv \sigma_v^2 = \sigma_\mu^2 \left(I_I \otimes \iota_T\right) + \sigma_\lambda^2 \left(I_T \otimes \iota_I\right) + \sigma_\varepsilon^2 \left(I_I \otimes I_T\right) \tag{9}$$

where I_I and I_T (ι_I and ι_T) represent an identity matrix (vector of ones) of (T and I dimensions (T and I dimensions), respectively.

The theta's are defined as

$$\theta_1 = 1 - \left(\frac{\sigma_\varepsilon}{\varphi_2^{1/2}}\right), \theta_2 = 1 - \left(\frac{\sigma_\varepsilon}{\varphi_3^{1/2}}\right), and \theta_3 = \theta_1 + \theta_2 + \left(\frac{\sigma_\varepsilon}{\varphi_4^{1/2}}\right) - 1 \tag{10}$$

The $\varphi's$ - $\hat{\varphi}_2 = T\sigma_\mu^2 + \sigma_\varepsilon^2$, $\hat{\varphi}_3 = N\sigma_\lambda^2 + \sigma_\varepsilon^2$ and $\hat{\varphi}_4 == T\sigma_\mu^2 + N\sigma_\lambda^2 + \sigma_\varepsilon^2$ are obtained from between cross-section $\left(\sigma_\mu^2\right)$, between time-period (σ_λ^2) and within cross-section time-period (σ_ε^2) variances of random errors and one-sided errors (efficiency). The $\varphi's$ used in the computation of the thetas (θ_1, θ_2 and θ_3) can be estimated using

1) Pooled stochastic frontier production function model residuals or one-sided efficiency as in the WH approach (1969);

2) Within stochastic frontier production function model residuals or one-sided efficiency as in the AM approach (1971) or

3) Between cross-section, between time-series and within cross-section time-series stochastic frontier production function model residuals or one-sided

efficiency as in the SA approach (1972).

Pitt and Lee (1981) proposed the use of the random and one-sided errors of the SFA to transform variables to estimate alternative one-way random effects panel models. However, the statistical theory associated with two-way random effects model is empirically very hard to estimate. Here, two sets of alternative two-way random effects panel SFA estimators are proposed. The first set uses between cross-section $\left(\sigma_\mu^2\right)$, between time-period (σ_λ^2) and within cross-section time-period (σ_ε^2) variances estimated from the random error (v) of the pooled SFA model. The second set uses the between cross-section $\left(\sigma_\mu^2\right)$, between time-period (σ_λ^2) and within cross-section time-period (σ_ε^2) variances estimated from one-sided error (u) of the within SFA model. The SFA module in LIMDEP or STATA package is used to estimate two-way random effects stochastic frontier production function as follows

1) Estimate pooled and within cross-section time-series stochastic frontier production function model with heterogeneity in the random error, v_{it}, and the one-sided inefficiency, u_{it}. Specifically, estimate stochastic frontier model of y_{it} on x_{it} for pooled (Wallace-Hussain) and $\tilde{y}_{it}$ on $\tilde{x}_{it}$ for within (Amemiya), where $\tilde{y}_{it} = y_{it} - y_{i.} - y_{.\,t} + y_{..}$.

2) Obtain the error variance σ_ε, σ_μ and σ_λ to develop $\hat{\varphi}_2$, $\hat{\varphi}_3$ and $\hat{\varphi}_4$ to estimate the thetas, θ_1, θ_2, θ_3 in order to transform the output and input variables,y_{it}^*, and x_{it}^* respectively, i.e., $y_{it}^* = y_{it} - \theta_1 y_{i.} - \theta_2 y_{.\,t} + \theta_3 y_{..}$ (see equation 10).

3) Finally, estimate alternative panel estimators of stochastic frontier production function model with heterogeneity in the random error,v and the one-sided inefficiency, u using WH and AM transformed data.

3 Data and Variables used in the Analysis

The U.S. Department of Agriculture's Economic Research Service constructs and publishes the U.S. and state farm production accounts. The aggregate *output* quantity index and six input quantity indexes are used to estimate the primal production function using SFA. The six inputs include - *land*, *labor*, *capital*, *chemicals*, *energy* and *material* input quantity indexes. Since, state level data on DGP[4] and CIP are available in dollars, implicit quantity indexes of DCP and CIP are computed. The interest is to evaluate the effects of short and long-run variability in DGP and CIP on efficiency and productivity. The short-run variability of real DGP ($dgpSR$) and CIP ($cipSR$) is computed as a five-year rolling window standard deviation. Five-year moving standard deviation is used so that it corresponds to the introduction of a farm bill approximately every five years. The long-run variability is computed as the cumulative standard deviation of real DGP ($dgpLR$) and CIP ($cipLR$) starting with 5 years and cumulating over 45 years.

[4] According to U.S. Department of Agriculture, direct government payment is the payments to producers for programs administered by Farm Service Agency or Natural Resources Conservation Service and paid by Farm Service Agency-Calendar Year Report of Payments to Producers by State and Category (MS-241R) from Farm Service Agency; Payments to producers for programs administered and paid by Natural Resources Conservation Service-Fiscal Year Report of Monthly Payments to Producers by State and Category from Natural Resources Conservation Service.

< Insert Table 1 and Figures 3 to 4 >

Table 1 summarizes the mean, standard deviation, minimal and maximal values for the output, six inputs, DGP and CIP short-run risk and DGP and CIP long-run risk used in this analysis. All the variables are quantity index consistent with the production theory that suggests the use of input and output quantities. Figure 3 shows the trends in output quantity index, DGP implicit quantity index and CIP implicit quantity index by state from 1960 to 2004. Similarly, Figure 4 shows trends in six input quantity indexes by state from 1960 to 2004.

4 Empirical Application and Results

To examine the importance of short- and long-run variability in DGP and CIP on efficiency and productivity variance, the stochastic frontier model with heterogeneity in the random error, and the one-sided inefficiency, as defined in equation (7) is estimated. Secondly, the WH and AM[5] panel stochastic frontier production function with heterogeneity in the random error, and the one-sided inefficiency, as defined by equation (8), is used to estimate variance in DGP and CIP. In addition, the WH and AM panel double heterogeneity stochastic frontier production function is estimated under the assumption of gamma[6] distribution.

The output and inputs in the production function equation are estimated using

[5] In addition to WH and AM panel stochastic frontier production function models, the Swamy-Arora (SA) panel stochastic frontier production function model is also estimated and the results are available from the authors.

[6] Half-normal and truncated normal distribution of one-sided error term results are also estimated and available from the authors.

the logs of the variables. The short- and long-run DGP and CIP variability in inefficiency and productivity variance function is estimated in levels. Gamma stochastic frontier analysis of the production function with double heterogeneity is estimated following Greene (2007).

A Cobb-Douglas[7] functional form for the pooled, time-series, cross-section, WH and AM panel gamma stochastic frontier models with heterogeneity in the random error (v) and the one-sided inefficiency (u) is specified. The long- and short-run variance of DGP and CIP is specified in the inefficiency and productivity heteroskedasticity variance function. The Cobb-Douglas functional form with heteroskedasticity is specified as

$$
\begin{aligned}
Output_{it} &= \beta_0 + \beta_1 Capital_{it} + \beta_2 Land_{it} + \beta_3 Labor_{it} + \beta_4 Chemicals_{it} \\
&\quad + \beta_5 Energy_{it} + \beta_6 Materials_{it} + \beta_7 Year + \varepsilon_{it} \\
\sigma^2_{\mathrm{u}} &= \gamma_{0,u} + \gamma_{1,u} dgpSR_{it} + \gamma_{2,u} dgpLR_{it} + \gamma_{1,u} cipSR_{it} + \gamma_{2,u} cipLR_{it} \\
\sigma^2_{\mathrm{v}} &= \gamma_{0,v} + \gamma_{1,v} dgpSR_{it} + \gamma_{2,v} dgpLR_{it} + \gamma_{1,v} cipSR_{it} + \gamma_{2,v} cipLR_{it}
\end{aligned} \tag{11}
$$

4.1 Pooled and Within Stochastic Frontier Production Function

Parameter estimates of the pooled and within gamma stochastic frontier production function are presented in table 2. In addition to showing the variables related

[7] A more flexible functional form, the Translog production function is also estimated. However, the input elasticities and returns to scale was not in the normal range with and without imposing the properties of production function including curvature conditions. Apart from these out of range results and the main focus of the paper is to illustrate the importance of short- and long-run variability in DGP and CIP on efficiency and productivity so a simple functional form is used in the empirically estimation.

to production function, the table also demonstrates the impact of short- and long-run variations in DGP and CIP variables due to the heterogeneity in the random error (v) and the one-sided inefficiency (u) specification related to production function. The independent and dependent variables are in logarithms, hence, the coefficients of the production function represents elasticity of inputs with respect to output.

< Insert Table 2 >

Results in table 2 suggest that the pooled and within SFA production function performs well. The year, as a proxy for technology, is positively related to agricultural output, with returns to scale of 0.842 (0.755) for pooled (within) SFA production function model. The theta, p, and sigma (v) is positive and significant in both the models. In each case, the input variables in the production function are all positive and statistically significant at the one percent level of significance. An interesting finding here is that, the estimated coefficients of short- and long-run variability in CIP is similar in pooled and within SFA models. However, the estimated coefficients of DGP are different in pooled and within models. Results indicate material input elasticity of 0.415 (0.35) in pooled (within) SFA model suggests a 100 percent increase in the use of material input increases output by 41.5 (35) percent. The second factor with a significant impact on agricultural production in the US is energy (chemical) for the pooled (within) SFA model. Results in table 2 indicate an input elasticity of energy (chemical) of 0.172 (0.134) indicating that a 100 percent increase in energy (chemical) input would increase the output by 17.2 (13.4) percent.

The capital, chemical and labor ranks third (0.084), fourth (0.069) and fifth (0.053) with respect to the magnitude of contributions to agricultural output, based on the results from the pooled SFA model. The land variable was positive but not statistically significant. For the within SFA model, energy, capital, land and labor ranks third (0.125), fourth (0.107), fifth (0.025) and sixth (0.011) with respect to the contribution to agricultural output production. All the input variables are positive and statistically significant.

The pooled SFA model results indicate the short-run CIP and long-run DGP is negative and positive, respectively, but statistically insignificant on inefficiency. However, the short-run DGP and the long-run CIP variable in the inverse of inefficiency variance function is positive and statistically significant. The positive sign indicates an increase in short-run DGP and long-run CIP variability increases inefficiency. This suggests variability in DGP and CIP would negatively impact efficiency as they are built into producers' expectations in the short- and long-run, respectively.

The short-run DGP and CIP variable is negative and significant at the 1 percent level of significance on inefficiency for the within SFA model. The negative sign indicates that short-run variation in DGP and CIP would decrease variation in the inverse of inefficiency variance. This result suggests producers would be able to withstand short-run variability and still be efficient in production. However, the positive and statistically significant long-run variability in DGP and CIP suggest producers cannot be efficient in production. This is due to the long-run uncertainty in the flow of DGP and CIP payments that forms part of the decision making process of the producers.

The impact of short- and long-run variability in DGP and CIP on productivity is different for the pooled and within SFA models. With respect to the pooled model, all the variables are statistically insignificant. However, the within SFA model suggests negative effect of short-run CIP, long-run CIP and long-run DGP variability on productivity. In contrast, the short-run DGP variability has a positive effect on productivity, suggests producers are able to overcome short-run variation and still be productive.

Overall, the results are mixed not only with respect to pooled and within models but also efficiency and productivity measures. Next, WH and AM panel SFA models that account for spatial and temporal variation using variances estimated from pooled and within random errors (v) and one-sided errors or efficiency (u) are presented.

4.2 Panel Stochastic Frontier Production Function

In exploring alternatives to the pooled frontier production function, we now switch to estimating panel stochastic frontier production functions with heterogeneity in the random error (v) and the one-sided inefficiency (u). In particular, we estimate panel stochastic frontier production functions using WH and AM two-way random effects panel estimators.

< Insert Table 3 >

The transformation of the variables to estimate panel model require the estimation of theta's, lambda's and variances. The WH model uses the pooled random error (v) and the one-sided inefficiency (u), while the AM model uses the within random error (v) and the one-sided inefficiency (u) to compute the theta's, lambda's and variances. The theta, lambda and variance values for the pooled and within models using random error (v) and the one-sided inefficiency (u) are presented in Table 3. Results from Table 3 suggest, the use of efficiency measures to compute the thetas, lambdas and variances used to transform the variables always guarantees non-zero values. However, the use of traditional random errors leads to zero values due to truncation of negative values at least with the AM model. To guarantee non-zero thetas, lambdas and variances it is appropriate to use one-sided errors or efficiency to transform the variables. Parameter estimates of the WH and AH panel gamma stochastic frontier production function are presented in Table 4.

< Insert Table 4 >

Table 4 presents results from the WH and AM alternative panel stochastic production frontier model with heterogeneity in the random error (v_{it}) and the one-sided inefficiency (u_{it}). In addition to the traditional input factors, we also assess the impact of short- and long-run variations in DGP and CIP on efficiency and productivity variance. Comparing the overall result between pooled and panel stochastic frontier production function indicates that the coefficients of the inputs are different not only between the WH and AM models but also between efficiency and residuals used to transform the variables. In the case of variations in DGP and CIP (both short- and long-run) - inefficiency and productivity variations-results show that the signs on the coefficients are different between WH and AM. Within WH models, the sign but not the magnitude are similar between WH efficiency and WH residual models. The AM alternative panel stochastic production frontier model indicates the short- and long-run variations in DGP and CIP variables do not statistically effect efficiency and productivity. Hence, the rest of the discussion is based on the WH alternative panel stochastic production frontier model with heterogeneity in the random error (v_{it}) and the one-sided inefficiency (u_{it}).

Results in table 4 suggest that year, as a proxy for technology, is positively related to agricultural output, with returns to scale of 0.709 (0.745) for the WH efficiency (WH residual) transformed panel stochastic frontier model. Relative to the WH alternative panel models, the pooled model overestimates returns to scale to the U.S. agriculture. The theta, p and sigma(v) are all positive, statistically significant and similar in magnitude for WH efficiency and WH residual models. The shape parameter, p is also significant for the pooled and panel estimators. Larger values of p (greater than 1) allow the mass of the inefficiency distribution to move away from zero. Results indicate that for the pooled and most of panel models, the value of p was less than or close to zero.

The WH efficiency transformed panel stochastic frontier results indicate that input elasticities are all positive and significantly related to the output with the exception of capital (negative and significant) in the WH residual model. The production function results are consistent with production theory, i.e., an increase in the quantity of input leads to an increase in the quantity of output produced. The results from the WH efficiency and WH residual panel models indicate an input elasticity of about 0.382 and 0.417, respectively, for materials is relative higher than other inputs. This indicates, a 100 percent increase in material inputs would increase the output by 38.2 percent and 41.7 percent, respectively for the WH efficiency and WH residual models. The coefficient on chemical input is about 0.115 and 0.111 for the WH efficiency and WH residual models, respectively. It should be noted that chemical input ranks second with respect to the magnitude of contributions to agricultural output, indicating that a 100 percent increase in chemical input increases agricultural output by about 11.5 and 11.1 percent, respectively, for the WH efficiency and WH residual models. For the WH efficiency model, energy is followed by labor, capital and land, indicating labor and capital inputs have smaller positive influence on agricultural output.

With respect to the WH alternative panel stochastic frontier production model, the effect of short- and long-run variations in DGP and CIP on efficiency is relatively greater than productivity. The final four rows in table 4 assess the impact of long- and short-run variations in DGP and CIP on productivity. The short- and long-run variation in CIP and long-run variation in DGP is negative and significantly related to productivity. This suggests decreased variation in agricultural productivity with increased short- and long-run variation in CIP and long-run variation in DGP. This could be due to the short- and long-run upside variation over and above the mean. However, an increase in short-run variation in DGP is the only variable that would increase variation in agriculture productivity.

The effect of short- and long-run variation in DGP and CIP on inefficiency is much more consistent between the WH efficiency and WH residual panel stochastic frontier production models. The short-run variation in DGP and CIP is negative and statistically significant. This suggest, producers in the U.S. are able to withstand short-run variations in DGP and CIP and still able to produce efficiently. This could be due to the ability of the producers to overcome short-run variations in expected DGP and CIP. However, the results in table 4 show that the impact of long-run variation in DGP and CIP is positive and statistically significant at the 1 percent level of significance. This suggest, the producers have already built-in the expected DGP and CIP into their decision making process and expected profits in the long-run due to huge investments on their farm.

Finally, the estimated theta and sigma for pooled and SA panel estimator are significant at the 1 percent level of significance. This result indicates a good fit of the gamma pooled and panel model with heteroskedasticity in one-sided and random errors.

5 Conclusion

The contribution of the research presented here is twofold. First, WH and AM alternative two-way random effects panel estimators of the normal-gamma stochastic frontier model with heterogeneity in the random error (v) and the one-sided efficiency (u) is proposed. In particular, we propose a generalized least squares procedure that involves the use of random error (v) and one-sided efficiency (u) to estimate the variances and then using the estimated variance-covariance matrix to transform the data is proposed. The data transformation involves estimation of the within residuals and efficiency for the AM panel estimator and pooled residuals and efficiency for the WH panel estimator. Secondly, the stochastic frontier model with heteroskedasticity of a random error term (v) identified with productivity and a one-sided error term (u) identified with inefficiency, is used to examine the importance of short- and long-run risk or variability in DGP and CIP.

Empirical estimates indicate differences in the parameter estimates of production function and heterogeneity function variables between pooled and WH or AM panel estimators. The difference between the pooled and the panel SFA model suggests the need to account for spatial, temporal, and within residual variations as in WH or AM panel estimator. Findings from this study show production increases with increasing units of inputs. Results from this study indicate that short- and long-run variation in DGP and CIP plays a positive and negative role, respectively, on inefficiency. In contrast, only the short variation in DGP plays a negative role on productivity.

In the future research the robustness of the alternative two-way random effects models is being evaluated using USDA farm-level data. In addition, the use of farm data by region with disaggregate data on different kinds of federal farm programs and commodities grown would be helpful to policy makers.

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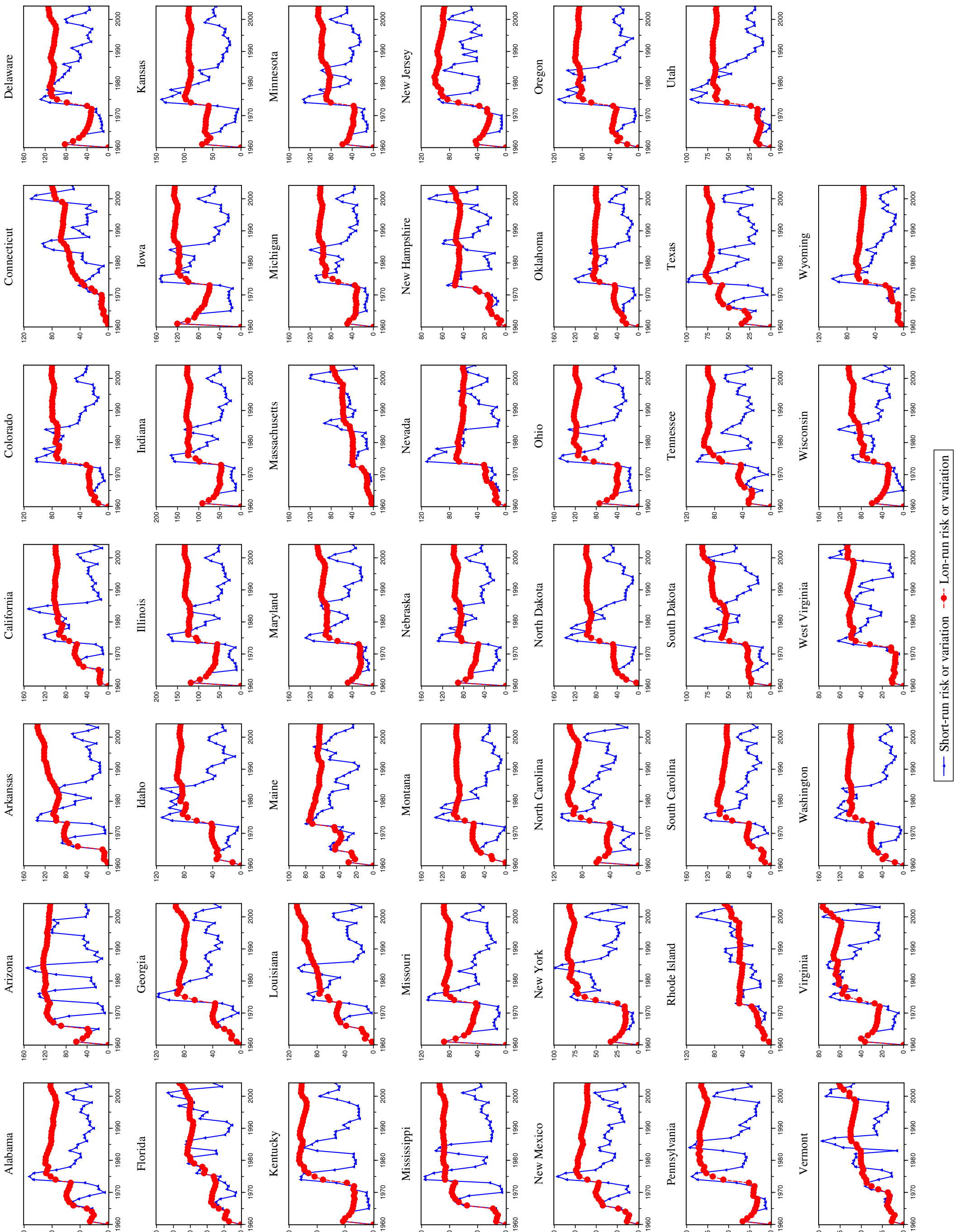

Figure 1: Short and Long-run Variability in Direct Government Payments, 1960-2004

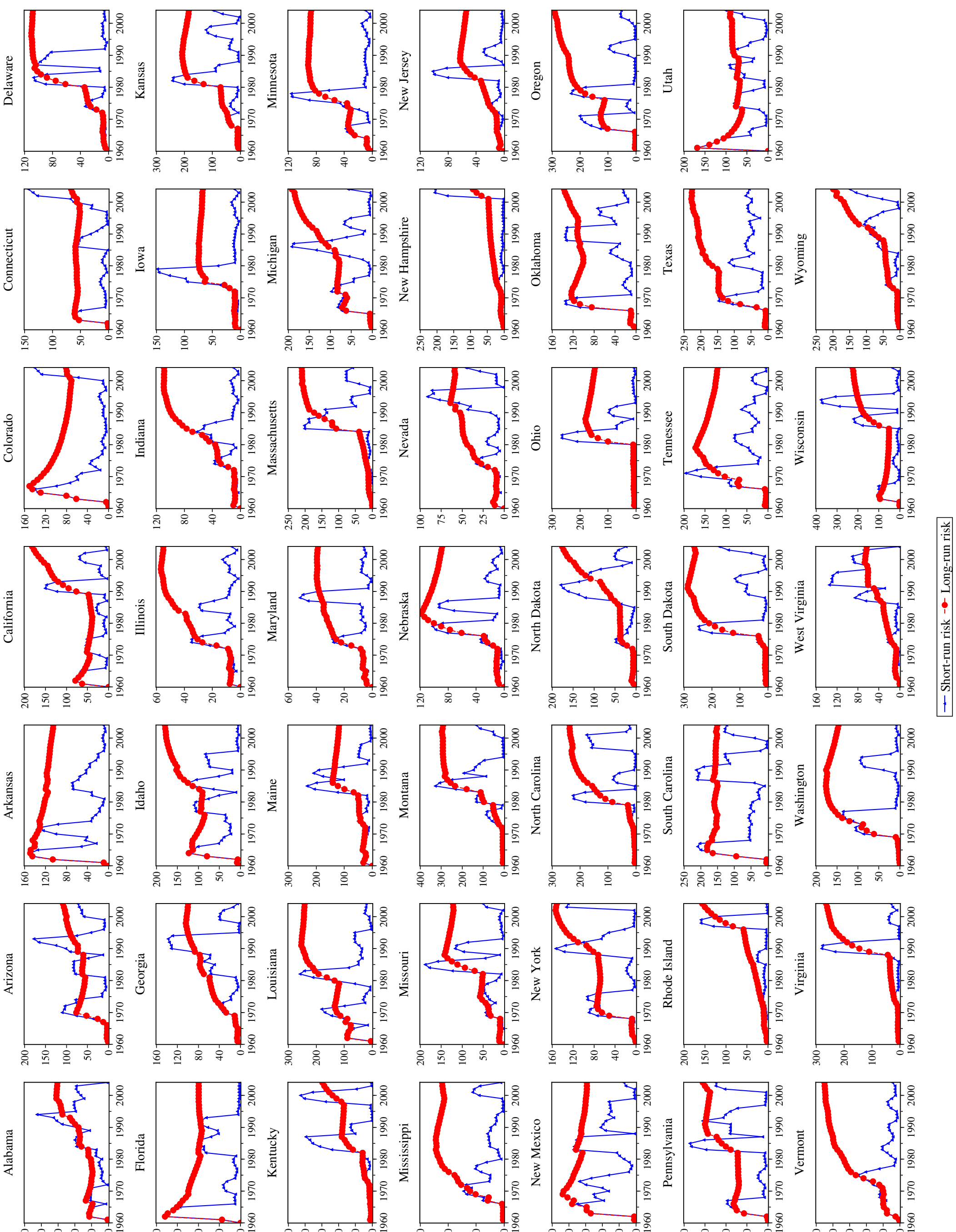

Figure 2: Short and Long-run Variability in Crop Insurance Programs, 1960-2004

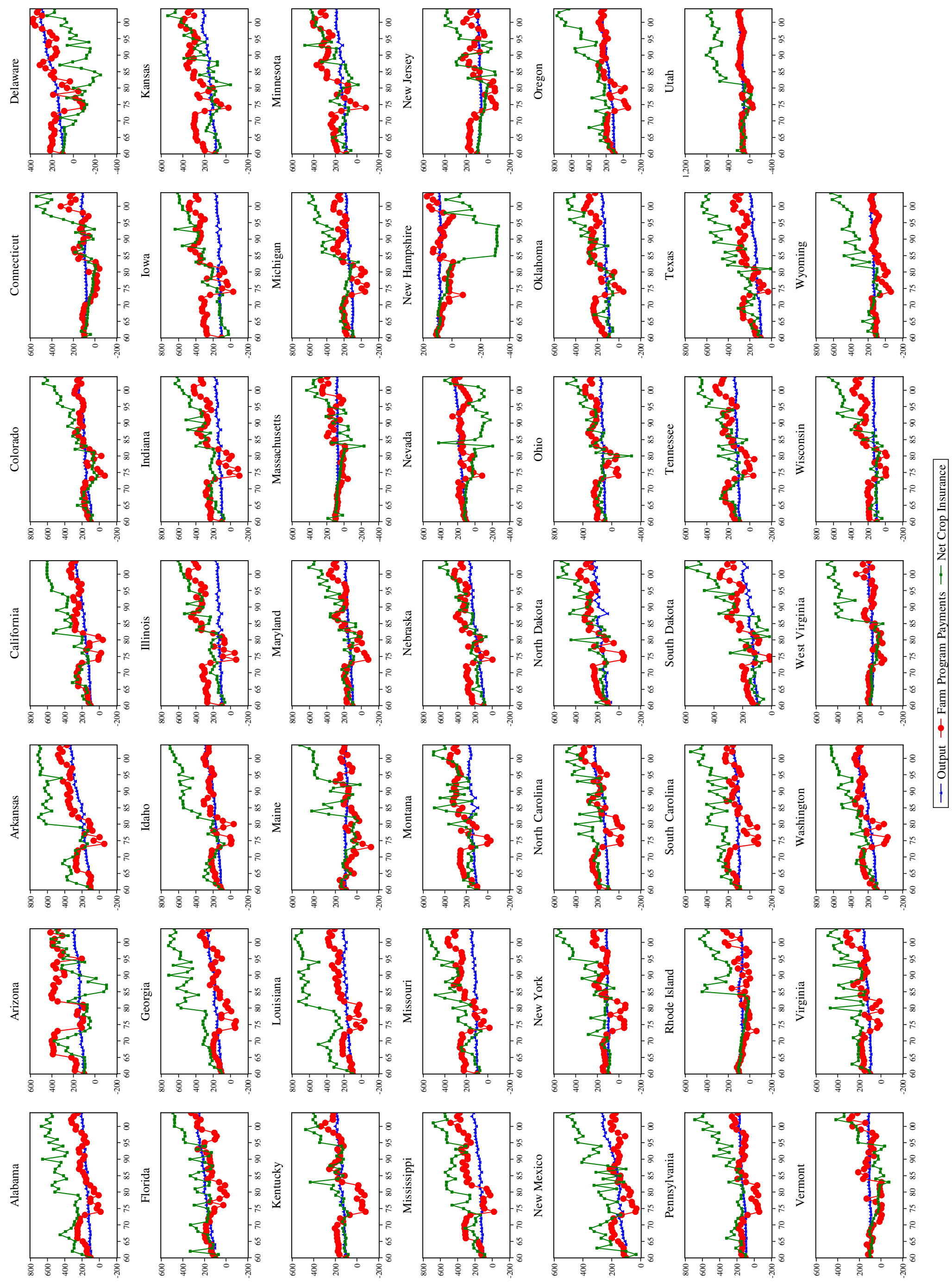

Figure 3: Trends in Output, Farm Program Payments and Net Crop Insurance Quantity Index, 1960-2004

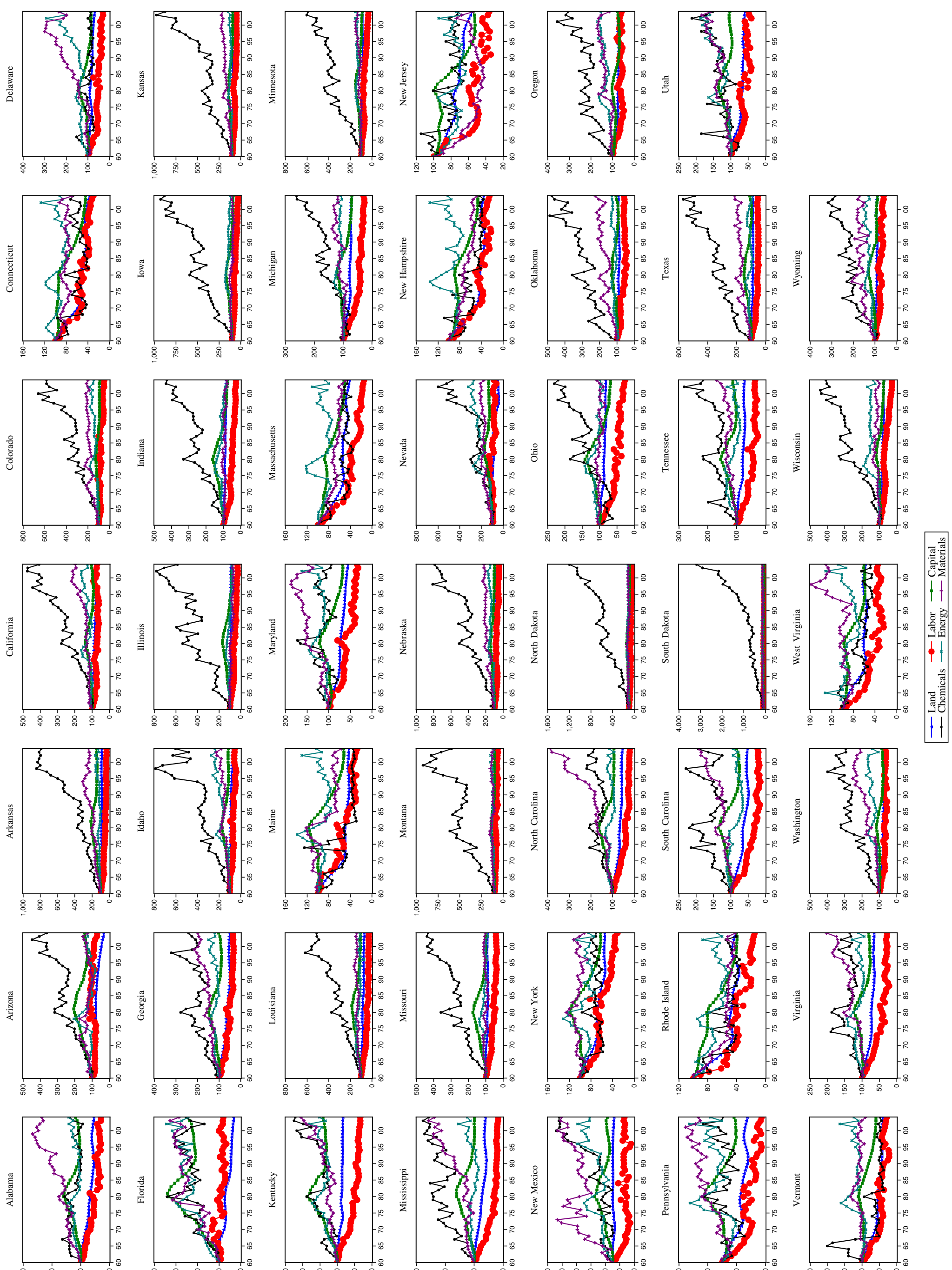

Figure 4: Trends in Land, Labor, Capital, Chemical, Energy and Material Input Quantity Index, 1960-2004

Table 1: Summary Statistics of Output, Inputs, DGP and CIP variables

	Mean	Std. Dev.	Minimum	Maximum
Output	141.17	47.77	59.52	336.10
Land	80.42	17.36	33.57	104.96
Labor	59.50	22.15	14.39	134.60
Capital	107.56	27.87	39.38	219.24
Chemicals	228.74	219.69	28.82	3,180.54
Energy	118.31	31.18	51.79	322.73
Materials	129.86	46.48	41.58	388.40
Short-run DGP variability ($dgpSR$)	43.92	31.06	0.00	172.24
Long-run DGP variability ($dgpLR$)	68.65	31.90	0.00	134.69
Short-run CIP variability ($cipSR$)	47.14	31.85	0.00	262.28
Long-run CIP variability ($cipLR$)	77.10	44.18	0.00	228.81

Table 2: Pooled and Within Stochastic Frontier Production Function with Gamma Distribution

	Pooled		Within	
Variable	Coefficient	Prob. |z|>Z	Coefficient	Prob. |z|>Z
Constant	0.732	< 0.001	0.020	< 0.001
Land	0.036	0.126	**0.025**	< 0.001
Labor	**0.053**	0.000	**0.011**	< 0.001
Capital	**0.084**	< 0.001	**0.107**	< 0.001
Chemical	**0.069**	< 0.001	**0.134**	< 0.001
Energy	**0.172**	< 0.001	**0.125**	< 0.001
Material	**0.415**	< 0.001	**0.350**	< 0.001
Technology	**0.013**	< 0.001	**-0.0003**	< 0.001
Gamma Shape parameters				
Theta	**41.692**	0.038	**25.755**	< 0.001
P	**1.471**	0.000	**0.313**	< 0.001
Sigmav	**0.122**	< 0.001	**0.053**	< 0.001
Heterogeneity in the Inefficiency				
cipSR	-0.233	0.438	-19.421	< 0.001
cipLR	**0.714**	0.054	7.102	< 0.001
dgpSR	**0.294**	0.084	-8.230	< 0.001
dgpLR	0.012	0.935	5.252	< 0.001
Heterogeneity in the Productivity				
cipSR	-0.027	0.693	**-2.220**	< 0.001
cipLR	-0.013	0.899	**-7.092**	< 0.001
dgpSR	-0.063	0.336	**0.788**	< 0.001
dgpLR	0.072	0.218	**-2.925**	< 0.001

Table 3: Parameters for Transformation of Variables from Gamma Distribution

		Gamma distribution	
	Parameters	Wallace-Hossain	Amemiya
Residuals	theta1	0.8957	0.3943
Residuals	theta2	0.7539	0
Residuals	theta3	0.7461	0
Residuals	lamda1	0.0048	0.0069
Residuals	lamda2	0.4432	0.0187
Residuals	lamda3	0.0796	0.0069
Residuals	lamda4	0.518	0.0187
Residuals	sig2v	0.0048	0.0069
Residuals	sig2m	0.0115	0.0003
Residuals	sig2l	0.0016	0
Efficiency	theta1	0.8323	0.4405
Efficiency	theta2	0.7471	0.5483
Efficiency	theta3	0.7206	0.3642
Efficiency	lamda1	0.0002	0.0287
Efficiency	lamda2	0.0079	0.0916
Efficiency	lamda3	0.0035	0.1405
Efficiency	lamda4	0.0112	0.2034
Efficiency	sig2v	0.0002	0.0287
Efficiency	sig2m	0.0002	0.0017
Efficiency	sig2l	0.0001	0.0023

Table 4: Wallace-Hussain and Amemiya Panel Stochastic Frontier Production Function with Gamma Distribution

	Wallace-Hussain				Amemiya			
	Efficiency		Residual		Efficiency		Residual	
Variable	Coefficient	Prob|z|>Z	Coefficient	Prob|z|>Z	Coefficient	Prob|z|>Z	Coefficient	Prob|z|>Z
Constant	**0.132**	< 0.001	**0.060**	< 0.001	**0.276**	< 0.001	**0.438**	< 0.001
Land	**0.023**	< 0.001	**0.071**	< 0.001	**0.061**	0.0053	**0.082**	0.0007
Labor	**0.047**	< 0.001	**0.056**	< 0.001	**0.056**	< 0.001	**0.071**	< 0.001
Capital	**0.031**	< 0.001	**-0.003**	< 0.001	**0.069**	0.0003	**0.052**	0.002
Chemical	**0.115**	< 0.001	**0.111**	< 0.001	**0.081**	< 0.001	**0.073**	< 0.001
Energy	**0.108**	< 0.001	**0.090**	< 0.001	**0.126**	< 0.001	**0.075**	< 0.001
Material	**0.382**	< 0.001	**0.417**	< 0.001	**0.428**	< 0.001	**0.443**	< 0.001
Trend	**0.004**	< 0.001	**0.003**	< 0.001	**0.006**	< 0.001	**0.013**	< 0.001
			Gamma Shape parameters					
Theta	**25.634**	< 0.001	**25.558**	< 0.001	**25.464**	< 0.001	**22.555**	< 0.001
P	**0.220**	< 0.001	**0.163**	< 0.001	**0.733**	< 0.001	**1.155**	0.0049
Sigmav	**0.073**	< 0.001	**0.065**	< 0.001	**0.084**	< 0.001	**0.077**	< 0.001
			Heterogeneity in the Inefficiency error					
cipSR	**-8.516**	< 0.001	**-4.298**	< 0.001	**-0.529**	0.0035	**-0.647**	0.056
cipLR	**3.883**	< 0.001	**1.922**	< 0.001	**0.683**	0.0526	**0.443**	0.098
dgpSR	**-2.363**	< 0.001	**-1.097**	< 0.001	-0.122	0.3899	0.204	0.1316
dgpLR	**2.031**	< 0.001	**1.111**	< 0.001	**0.334**	0.017	0.049	0.6691
			Heterogeneity in the Productivity error					
cipSR	**-0.842**	< 0.001	**-0.454**	< 0.001	0.099	0.1321	0.090	0.2097
cipLR	**-2.263**	< 0.001	**-1.006**	< 0.001	-0.157	0.105	0.090	0.463
dgpSR	**1.013**	< 0.001	**0.431**	< 0.001	-0.017	0.796	-0.029	0.716
dgpR	**-1.636**	< 0.001	**-0.759**	< 0.001	-0.046	0.5007	**0.135**	0.0831