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Does Accounting for Inefficiency affect the Time-Varying Short and Long-Run Returns to Scale?

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Abstract

The returns to scale for nineteen South Asian countries are estimated using window and cumulative rolling stochastic frontier regression analysis. The stochastic frontier analysis accounts for technical inefficiency of Hicks non-neutral technology production function in the estimation of the returns to scale. The window rolling regression and cumulative rolling regression allows the estimation of short and long run time-varying returns to scale, respectively. Empirical application to Asian agriculture sector using Food and Agricultural Organization data from 1961-2008 indicates returns to scale are under (over) estimated by the traditional panel models in the short (long) run time-varying estimation. The time-varying estimates of returns to scale indicate decreasing trend in the short run compared to long run analysis.

Keywords: Asian agriculture sector, stochastic frontier analysis, window and cumulative time-varying input elasticities and returns to scale, one-way fixed effect, 1961-2008.

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1 Introduction

Production economics, one of the fundamental pillars of neoclassical economics, has been the subject of intense research over the last century. At the macro-level, the focus has been on the use of aggregate production functions to explain technological progress, convergence, and factors contributing to economic growth. At the micro-level, economists use production functions to construct cost and profit functions, estimate the input elasticity[1], and compute returns to scale for a firm, sector, state, or country (Marschak, and Andrews, 1944; Bhattacharjee, 1955; Hoch, 1958, 1962; Zellner, Kmenta, and Dreze, 1966; Nerlove, 1963; Hayami and Ruttan, 1970; Diewert, 1974; Fuss, and McFadden, 1978; Nguyen, 1979; Yamada and Ruttan, 1980; Kawagoe and Hayami, 1983 and 1985; Antle, 1984; Kawagoe, Haymai, and Ruttan, 1985; Basu and Fernald, 1997; and Trueblood, 1991). In the post-World War II era, the focus of production function has been the analyses of cross-country productivity differences using parametric methods, linear programming and stochastic frontier analysis (Forsund, Lovell and Schmidt, 1980; Greene, 1993; Bureau, Fare and Grosskopf, 1995; Arnade, 1998; and Kumbhakar and Lovell, 2000).

Existing literature estimating production functions have computed the elasticity of inputs and reported the returns to scale without accounting for inefficiency[2]. Further, much of the earlier work in estimating production functions focused on the developed world where inefficiency, though present, was not of paramount interest. In developing or underdeveloped continents like Africa and Asia, the focus has been on poverty alleviation and food security, respectively. However, when estimating production function in developing or underdeveloped continents, accounting for inefficiency[3] is critical, particularly when assessing the impact of

[1]Input elasticity measures the rate of response of output due to input change and the summation of input elasticity provides the return to scale estimates.

[2]Efficiency concept introduced by Farrell (1957) is defined as the distance of the observation from the production frontier and measured by the observed output of a firm, state or country relative to realized output, i.e., output that could be produced if it were 100 % efficient from a given set of inputs.

[3]Ideally, there is a need to account for the overall inefficiency as well as input specific ineffi-

inputs and returns to scale due to green revolution.

This research first examines the importance of accounting for inefficiency on the elasticity of inputs and returns to scale. Stochastic frontier analysis (SFA) not only estimates the input elasticities but also accounts for inefficiency in the estimation of production function. However, is it necessary to account for inefficiency in the estimation of production function? The answer is yes, for the simple reason that the estimation of input elasticity and return to scale should be based on the efficient utilization of input resources to produce output after accounting for technology change. Accounting for inefficiency which was not done in production function estimation prior to the 1980s, leads to realization of true or accurate elasticity of inputs and returns to scale measures. If inefficiency is not accounted, it is possible to over or under estimate input elasticity in turn the return to scale. Second, apart from accounting for inefficiency there is also a need to estimate the short and long run time-varying elasticity of inputs, and returns to scale. Time-varying estimates represent one of the most widely used concepts in finance. The importance of time-varying estimates has been well established in the finance, risk, and time series literature (Rosenberg and Guy, 1976; Fisher and Kamin, 1985; Lawrence and Kamin, 1985; Chiang, 1988; Corckett, Nothaft and Wang, 1991; Groenewold and Fraser, 1999; Smith and Taylor, 2001). It is widely used by financial economist and practitioners to estimate the stocks sensitivity to the market and identify variations in stock prices.

In the context of production function, elasticity of inputs and returns to scale were assumed to be systematic (constant over time after accounting for technology changes) and driven by state, national and worldwide difference in the short and long run. But is it true to assume constant parameter coefficients over time when we observe short and long run variations. For example in India, there was enormous investment in development of high yield variety seeds during the green revolution. This was associated with use of fertilizers, construction of dams for

ciency measures. This could be accomplished by stepwise or input specific SFA estimation but would be biased and not efficient.

constant supply of water and expanding land use for agriculture. However, in recent years the quality of labor, seeds and chemicals has led to selective input resource usage. This would have differential implications in the short and long run. Hence, the systematic nature of the elasticity of inputs and returns to scale is questionable due to short and long run changes in the industry induced by advancements in structure of agriculture production. This paper aims to close this gap by empirically estimating the window and cumulative rolling regression to estimate short and long run time-varying input elasticity/returns to scale, respectively. The cumulative rolling regression allows the quantification of long run changes in the elasticity of inputs and returns to scale estimates with each additional year of data or information. The window rolling regression captures the short run changes in the elasticity of inputs and returns to scale estimates with dropping the earliest observation and adding new data or information.

Next, the short and long run time-varying stochastic production function frontier models are proposed along with the traditional panel production function model. In the data section, the details on the sources and construction of the regression variables along with their average and standard deviation are discussed. Results of empirical applications to Food and Agricultural Organization (FAO) data from 19 Asian countries forming the cross-sectional units over the period 1961-2008 with emphasis on the agricultural sector are presented next. Finally, general implications are presented.

2 Stochastic frontier production function econometric model

Depending on the availability of the data, returns to scale can be estimated for a single country using time series data or multiple countries using cross-sectional or for a group of countries using panel data. The production function can be represented by a linear Cobb-Douglas functional form. A generalized Hicks non-neutral[4] Cobb-Douglas production function can be represented as:

$$y_{it} = f\left(\left(x_{it}, x(t)_{it}; \beta\right), t\right) \cdot \varepsilon_{it} \tag{1}$$

where $i = 1, ..., I$ represent the cross-section units, i.e., countries and $t = 1, ..., T$, represents the time series, i.e., number of years, y denotes output produced from a vector of input,x, Hicks non-neutral technology change vector of input,$x(t)$, β the associated vector of parameter coefficients, t the time trend represents the Hicks neutral technology trend, and ε the error term. These parameter coefficients are the elasticity of inputs if the vectors of inputs and output are in logarithmic form.

The stochastic frontier model[5] that decomposes the error term, ε into random error, v and inefficiency[6], u can be represented as:

$$y_{it} = f\left(\left(x_{it}, x(t)_{it}; \beta_{sfa}\right), t\right) \cdot v_{it} - u_{it} \tag{2}$$

where β_{sfa} is the vector of stochastic frontier parameter coefficients, v_{it} represents firm and time-specific random errors which are assumed to be i.i.d. and normally distributed variables with mean zero and variance, σ_V^2; and u_{it} must be non-negative and one-side with variance,σ_V^2. The variables y and x are as defined in equation (1). The returns to scale are computed as the sum of the parameter

[4]Likelihood ratio test suggest the use of Hicks non-neutral technology change

[5]The stochastic frontier model, introduced by Aigner et al. (1977); Meeusen, van den Broeck (1977); and Battesse and Cora (1977) decomposes the error term, ε into random error, v and u inefficiency. Stochastic frontier analysis has become a popular tool to model the production relationship between input and output quantities and has been primarily used to estimate the technical efficiency of firms. In 1982, Jondrow et al. suggested a method to estimate firm specific inefficiency measures. Since it was introduced in 1977, the stochastic frontier analysis has been evolving theoretically with a surge in empirical application. Furthermore, progress has been made on extending to fixed effects, random effects and random parameters panel models, time invariant and time variant models, correcting for heteroskedasticity and heterogeneity and alternative distributions (normal- half normal, normal-exponential and normal-gamma) of technical inefficiency term. 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.

[6]Truncated, exponential and gamma distributed SFA models were also estimated but are not reported.

coefficients, β_{sfa} or the elasticity of inputs.

2.1 Time-varying stochastic frontier production function econometric model

To examine time-varying elasticity of inputs and the returns to scale, simple methods such as time dummies or testing for breaks using Chow tests, and separating the estimation into different periods have been used in the literature. To examine time-varying elasticity of inputs and the returns to scale, a window rolling regression and cumulative rolling regression of stochastic production function frontier is estimated to capture the short and long run changes. With cumulative rolling regression, a set of coefficients are estimated with each additional year of data. The cumulative rolling stochastic frontier production function can be re-written as:

$$y_{it}^{L} = f\left(\left(x_{it}^{L}, x(t)_{it}^{L}; \beta_{sfa}^{L}\right), t^{L}\right) \cdot v_{it}^{L} - u_{it}^{L} \tag{3}$$

where $L = 26, ..., T$ and represents the number of cumulative rolling stochastic frontier production function regression runs. The first regression starts with a window of the first 26 observations. The second regression includes an additional year of data; that is the first 27 observations. The third regression includes two additional years of data; that is the first 28 observations. The final regression would include all T years of data. This would be equivalent to the traditional regression analysis. With window rolling regression, a set of coefficients are estimated with each additional year of data and dropping data related to the earliest year. The window rolling stochastic frontier production function can be re-written as:

$$y_{it}^{S} = f\left(\left(x_{it}^{S}, x(t)_{it}^{S}; \beta_{sfa}^{S}\right), t^{S}\right) \cdot v_{it}^{S} - u_{it}^{S} \tag{4}$$

where s represents a constant number of years of data for each window rolling stochastic frontier production function regression run. The first regression starts with a window of the first 26 observations or years of cross-section units. The second regression includes adding an additional year and dropping the early year of data; that is 2 to 27 observations or years of cross-sectional units. The third regression includes adding an additional year and dropping the early year of data for the second regression run; that is 3 to 28 observations or years of cross-section units. Even though the number of years of data is constant, the composition of the window changes with time reflecting the short-run changes.

For comparison purpose, the cumulative and window rolling regression is also estimated using one-way fixed effect panel model as follows:

$$y_{it}^{L} = f\left(\left(x_{it}^{L}, x(t)_{it}^{L}; \beta_{sfa}^{L}\right), t^{L}\right) \cdot \varepsilon_{it}^{L} \tag{5}$$

and

$$y_{it}^{S} = f\left(\left(x_{it}^{S}, x(t)_{it}^{S}; \beta_{sfa}^{S}\right), t^{S}\right) \cdot \varepsilon_{it}^{S} \tag{6}$$

The short and long run analysis of Asian agriculture sector elasticity of inputs and returns to scale measures will provide insight into the economic performance accounting for any short and long-term variation. The results will also provide information that will be useful to policy makers for assessing the effects of variation on the elasticity of inputs and returns to scale.

Proposition 2.1 *Comparison of panel and stochastic frontier models allows the quantification of the difference (over or under estimation) in input elasticity and return to scale associated with accounting for inefficiency in the estimation of production function.*

Conceptually, over or under estimation of input elasticity and return to scale associated with accounting for inefficiency[7] using stochastic frontier analysis could be quantified by comparing the parameters estimated from panel and stochastic

[7]There are two issues associated with the derivative, $\partial y / \partial x_{ineff}$. First, examine what happens when over using inputs or not using inputs efficiently. Second, and not discussed in this paper: Parameter biases that may arise from not correctly specifying your estimating equations. This is an issue by itself and is not explored in this paper. For example, if the one side error relates to any of the inputs in the production function, then it is possible to end up with a parameter bias if you do not account for inefficiency. Battese and Coelli (1995) addressed this issue by relating one side error to variables.

frontier model. Earlier literature have examined one or the other methods and but did not compared the differences between methods. Comparison of stochastic frontier and panel model would be useful to evaluate the importance of accounting for inefficiency in the production function. Over or under estimation of input elasticity can be represented as:

$$\beta_{sfa} \gtreqless \beta = \frac{\partial y}{\partial x} \gtrless \frac{\partial y}{\partial \left(x + x_{ineff}\right)} \equiv \frac{\partial y}{\partial x} \gtrless \frac{\partial y}{\partial x} \pm \frac{\partial y}{\partial x_{ineff}} \tag{7}$$

where β_{sfa} and β are the parameter coefficients estimated from stochastic frontier and panel model, respectively. When dealing with inefficiency, β_{sfa} can be zero or negative due to the decomposed error structure assumptions of stochastic frontier analysis. The parameter, β from the panel model would be underestimated compared to β_{sfa} parameter from stochastic frontier model $ifandonlyif(iff)$ the inputs are actually or efficiently utilized in the production even after accounting for inefficiency. The panel model parameter, β would be overestimated compared to stochastic frontier model parameter β_{sfa} iff the inputs are actually utilized in the production but not efficiently. But this depends if the inputs are being used efficiently either due to the cost or regulations (for example clean air act of 1972 lead to the efficient use of chemicals and fertilizers). The β_{sfa} will be equal to β iff the same amount of inputs are utilized with and without accounting for inefficiency in the production function. The over or under estimation of parameter $(\beta_{sfa} - \beta)$ can be represented as:

$$(\beta_{sfa} - \beta) \Rightarrow \left\{ \begin{array}{lll} positive & \frac{\partial y}{\partial x} - \frac{\partial y}{\partial x_{ineff}} & ......iff\, the\, input\, is\, actually\, utilized\, but\, efficiently \\ Zero & \frac{\partial y}{\partial x} - 0 & ......iff\, x_{ineff}\, is\, zero \\ negative & \frac{\partial y}{\partial x} + \frac{\partial y}{\partial x_{ineff}} & .....iff\, the\, actual\, input\, is\, utilized\, but\, inefficiently \end{array} \right\} \tag{8}$$

Proposition 2.2 *Long (short) run time-varying parameter, $\beta^{L(S)}$ estimated from the equation 3 (4) allows quantifying the extent of long and short run input elas-*

ticity and return to scale.

Irrespective of the model (panel or stochastic frontier), the parameter estimates varies in the short and long run and this variation would be captured if the input and output variation is different than the earlier sample. Mathematically this can be represented as

$$\beta^{L(S)+1} \gtreqless \beta^{L(S)} = \frac{\partial\, y^{L(S)+1}}{\partial\, x^{L(S)+1}} \gtreqless \frac{\partial\, y^{L(S)}}{\partial\, x^{L(S)}} \equiv \frac{\partial\, \left(y^{L(S)} + y^{1}\right)}{\partial\, \left(x^{L(S)} + x^{1}\right)} \gtreqless \frac{\partial\, y^{L(S)}}{\partial\, x^{L(S)}} \tag{9}$$

The β^{L+1} estimated from production function with $L(S)$ observations plus one additional year of observation would be great than β estimated with $L(S)$ observations if the marginal effect, $\beta^1 = \partial y^1/\partial x^1$ is positive and greater than $\beta^{L(S)} = \partial y^{L(S)}\big/\partial x^{L(S)}$. The $\beta^{L(S)+1}$ parameter estimated from production function with $L(S)$ observations plus one additional year of observation would be less than $|beta$ parameter estimated with $L(S)$ observations if the marginal effect, $\beta^1 = \partial y^1/\partial x^1$ is negative and greater than $\beta^{L(S)} = \partial y^{L(S)}\big/\partial x^{L(S)}$. The β^{L+1} will be equal to β if the marginal effect, $\beta^1 = \partial y^1/\partial x^1$ is equal to zero. This can be represented as:

$$\beta^{L(S)+1} - \beta^{L(S)} \Rightarrow \left\{ \begin{array}{llll} positive & \left(\frac{\partial\, y^{L(S)}}{\partial\, x^{L(S)}} + \frac{\partial\, y^{1}}{\partial\, x^{1}}\right) & or \quad \left(\beta^{L(S)} + \beta^{1}\right) & ...iff\, \beta^{1}\, is\, positive \\ zero & \left(\frac{\partial\, y^{L(S)}}{\partial\, x^{L(S)}} + 0\right) & or \quad \left(\beta^{L(S)} + 0\right) & ...iff\, \beta^{1}\, is\, zero \\ negative & \left(\frac{\partial\, y^{L(S)}}{\partial\, x^{L(S)}} - \frac{\partial\, y^{1}}{\partial\, x^{1}}\right) & or \quad \left(\beta^{L(S)} - \beta^{1}\right) & ...iff\, \beta^{1}\, is\, negative \\ & & \&greater\, than\, \beta^{1} & \end{array} \right\} \tag{10}$$

The over or under estimation in input elasticity, $(\beta_{sfa} - \beta)$ and return to scale associated with accounting for inefficiency in the estimation of production function, and the extent of variation in the time-varying parameter with each additional year of information is empirically examined next.

3 Input and output Agriculture sector data for Asian Countries

This study is based on Food and Agricultural Organization data available online. The study includes 19 countries (Figure 1) for the period 1961 to 2008. For the output and the five inputs, the output quantity index and quantity of input resources used was constructed.

Figure 1: Map of the 19 countries of Southeast Asia

Due to the problems of estimating multiple outputs in primal production functions, an aggregate output variable published by FAO is used in the analysis. The FAO output concept is the output from the agriculture sector net of quantities of various commodities used as feed and seed, which is why feed and seed, are not included in the input series. Details on the construction of the aggregate output variable are available on FAO webpage, www.fao.org.

This analysis considers only five input variables following earlier studies estimating a production function. These variables include land, labor, capital, fertilizer and livestock. The land variable includes harvested acres of cereals, fibers, fruits, nuts, oil crops, pulses, roots and tubers, rubber, spices, stimulants, sugar crops, tobacco and vegetables unlike earlier studies that use land under cultivation. The capital variable covers the total number of agricultural tractors, and number of harvesters and threshers used in agriculture. With respect to tractors, no allowance was made to the quality (horsepower) of the tractors. The labor variable refers to the economically active population in agriculture. An economically active population is defined as all persons engaged or seeking employment in an economic activity, whether as employers, own-account workers, salaried employees, or unpaid workers assisting in the operation of a family farm or business. The economically active population in agriculture includes all economically active persons engaged in agriculture, forestry, hunting, or fishing. This variable obviously overstates the labor input used in agricultural production, but the extent of overstatement depends on the level of development of the country. Following other studies on inter-country comparisons of agricultural productivity, this analysis uses the sum of nitrogen, (N) potassium, (P2O2) and phosphate (K2O) contained in the commercial fertilizers consumed. This variable is expressed in thousands of metric tons.

The livestock input variable used in the study is the sheep-equivalent of five categories of animals. The categories considered are buffaloes, cattle, goats, pigs and sheep. The number of these animals is converted into sheep equivalents using conversion factors of 8.0 for buffalo and cattle and 1.00 for sheep, goats and pigs.

Chicken numbers are not included in the livestock figures.

Table 1 provides the means and standard deviations of the output and input index variables used in the analysis for the period 1961-2005.

4 Empirical Application and Results

Effect of accounting for technical inefficiency on the elasticity of inputs and returns to scale (Proposition 1) and short and long run time-varying estimates (Proposition 2) are examined using Cobb-Douglas Hicks non-neutral stochastic frontier production function[8]. Long and short run time-varying elasticity of inputs and returns to scale measures are recovered by estimating cumulative (equation 3) and window (equation 4) rolling stochastic frontier Hicks non-neutral production function, respectively. To compare the elasticity of inputs and returns to scale recovered from SFA to panel model equation (5 and 6) is also estimated. Alternative panel models one or two way fixed and random effects models accounting for autocorrelation and heteroskedasticity can be used to estimate the production function. Several possibilities exist for the estimation of one or two way random effects models in the traditional regression analysis. This includes the use of pooled OLS residuals (Wallace-Hussian estimator) within residuals (Amemiya estimator) or within residuals, between cross-sectional residuals and between time-series residuals (Swamy-Arora estimator). However, these alternative random effects models are not yet available in the SFA framework (exception, Shaik and Mishra, 2010). This research focuses on the one-way fixed effects[9] specification of the Cobb-Douglas Hicks non-neutral production function.

The one-way fixed effect Cobb-Douglas Hicks non-neutral production function

[8]Confidence interval of parameter coefficients of panel and stochastic frontier model for proposition 1 and 2 based on bootstrapping estimates are available upon request from the author. The bootstrapping estimate provides similar difference across panel and stochastic frontier models.

[9]One-way random effects, and two-way fixed and random effects models were also estimated.

can be econometrically represented as:

$$\ln y_{it} = \alpha + \sum_{k=1}^{5} \beta_k \ln x_{k,it} + \beta_t \, Trend + \sum_{k=1}^{5} \gamma_k \ln x(t)_{k,it} + \sum_{n=1}^{19} \lambda_{n-1} CS\, dummy_{it} + \varepsilon_{it} \tag{11}$$

Similarly, the one-way fixed effect Cobb-Douglas Hicks non-neutral stochastic frontier production function can be econometrically represented as:

$$\ln y_{it} = \alpha + \sum_{k=1}^{5} \beta_k \ln x_{k,it} + \beta_t \, Trend + \sum_{k=1}^{5} \gamma_k \ln x(t)_{k,it} + \sum_{n=1}^{19} \lambda_{n-1} CS\, dummy_{it} + v_{it} - u_{it} \tag{12}$$

where β_k represents the elasticity of inputs and the sum represents returns to scale, β_t represents Hicks neutral (HN) technology change, γ_k represents the input specific Hicks non-neutral (HNN) technology change and the sum represents HNN change, and λ_{n-1} represents $n-1$ individual country dummies.

Long and short run set of results are presented for panel and SFA models using logarithms of the input and output variables. A nice feature about using logarithms is that the slope coefficient measures the elasticity, that is, percentage change in output given a percentage change in input. Result of proposition 1 is presented in tables 2 to 4, and results of proposition 2 are presented in tables 5 and 6, and graphically in figures 1, 2 and 3.

Proposition 4.1 *Comparison of panel and stochastic frontier models allows the quantification of the difference (over or under estimation) in input elasticity and return to scale associated with accounting for inefficiency in the estimation of production function.*

Over or under estimation of elasticity of inputs, HN trend and HNN input change, and returns to scale associated with accounting for inefficiency is examined by comparing the stochastic frontier production function and panel model. Table 2 presents the average and standard deviation of the time varying parameter coefficients estimated from window (short-run) and cumulative (long run) regression runs. Not all the short-run time varying parameter coefficients are significant in the panel and SFA model. However, the SFA model has more statistically significant parameter coefficients than panel model. In general, all the input variables are positive and significant for the window (short-run) regression model. However, the inputs with Hicks non-neutral technology are negatively related with the exception of labor and fertilizer. The Hick neutral technology trend was negative related to output in the window (short-run) regression models. In contrast for the cumulative (long-run) regression models, all the input variables and the Hicks neutral technology trend are positive and significantly affect agricultural output with the exception of fertilizer. The fertilizer variable is negative and significant for the panel and SFA models. The inputs with Hicks non-neutral technology are positively related with the exception of land and capital.

First, the results from the SFA model indicate an input elasticity of 0.44 (0.28) for land which is the highest (second) relative to the other inputs in the long-run (short-run). Land elasticity of 0.44 and 0.28 seems to be consistent with earlier estimates that range 0.02 to 0.42 (see table 1 from Mundlak, Larson and Butzer, 1997). A 100 percent increase in the allocation of land to agriculture would increase the output by 44 and 28 percent, respectively in the long and short run, which indicates more agricultural products can be produced when more land is under agricultural production. Difference between the short and long run suggests land contributes more to the output in the long compared to the short run. Similar results for labor (capital) suggest an increase in farm labor (capital) would contribute to higher output by 17 and 39 percent (4 and 8 percent) respectively in the short-run and long-run. The labor elasticity is consistent with earlier estimates that range from 0.03 to 0.46 (see table 1 from Mundlak, Larson and Butzer, 1997). Livestock with an input elasticity of 0.37 (0.39) is ranked third (first) after land and farm labor in the long (short) run. A 100 percent increase in the availability of livestock on the farm would increase the output by more than 30 percent in both the short and long run.

Hicks non-neutral technological changes in land and capital are negatively related to output in the short and long run analysis. This suggests the technological changes associated with land and capital is declining even though they are positively used in the production of output. In the short run even the technological changes in the livestock is changing due to the substitution of capital for livestock in Asian farming. In contrast the Hicks non-neutral technological changes in labor and fertilizer is positively associated to production suggesting there is investments in these input that is contributing to higher output in Asian countries. Hicks neutral technology trend variable is negatively related to the output in the short run compared to the positive effect long run and is a reflection of the changes in recent years.

The panel short and long run results are similar with SFA results. So instead of detailed panel results, a comparison between panel and SFA model results would reveal the importance of accounting for inefficiency in the estimation of production function. Table 3 and 4 presents the ratio of the SFA to panel models results for the short and long run time-varying estimates, respectively.

With short run time-varying estimates, labor and livestock input elasticities are always underestimated by the panel compared to SFA model with one exception (see table 3). This suggest two things first the inputs are used inefficiently and second even after accounting for inefficiency in the estimation of production function, higher values seem to reflect the higher usage of labor and livestock in the production of output leading to higher return to scale measure. Similar lower land and capital elasticity measures were estimated by panel model. However, the trend reversed in recent years suggesting inefficient use of land and capital. Hence accounting for inefficiency in the production function lead to lower land and capital elasticity measures in SFA compared to panel model. Fertilizer was exactly opposite of land and capital, in the sense SFA model underestimated the fertilizer measures in the earlier years and overestimated in the latter years.

These results are quite interesting as they suggest that fertilizer is overused due to the prevalence of wetland rice in Asian agriculture and introduction of new green revolution seed and technology. However in recent years with increase cost and environmental awareness (regulations), there is more efficient application and use of fertilizer in Asian countries.

Hicks non-neutral technological changes in land, labor, capital, livestock and Hicks neutral technology trend was overestimated by SFA earlier and underestimated in recent years. These results suggest the technology induced input use is more inefficient in recent years. Overall the return to scale is underestimated by panel model as inefficiency is not accounted in the estimation of production function.

Table 4 presents the ratio of the SFA to panel models results for long run time-varying estimates. Long run time-varying labor, capital, livestock, fertilizer, and Hicks neutral technology trend measures suggest the panel model underestimates (overestimates) in the earlier (later) years. While the Hicks non-neutral technological changes in land, labor, capital, livestock and fertilizer, the SFA model always overestimates the contribution to agriculture output. Overall the return to scale is under (over) estimated by panel model in the earlier (later) years as inefficiency is not accounted in the estimation of production function.

Proposition 4.2 *Long (short) run time-varying parameter, $\beta^{L(S)}$ estimated from the equation 3 (4) allows quantifying the extent of long and short run input elasticity and return to scale.*

Tables 5 and 6 presents the time-varying parameter coefficients estimated from stochastic frontier window and cumulative rolling regression analyses of 24 runs from 1986 to 2008. The mean, minimum, and maximum values in the time-varying elasticity of inputs, technical change and return to scale are also presented in the tables. The land, labor, capital, fertilizer, and livestock estimated from the stochastic frontier window and cumulative rolling regression model is graphically presented in figure 1. The Hicks non-neutral technology land, labor, capital, fertilizer, and livestock are graphically presented in figure 2. Finally, the Hicks neutral technology trend, sum of Hicks non-neutral technology and returns to scale is graphically presented in figure 3.

Results from table 5 indicate the mean elasticity of land from stochastic frontier window rolling regression analysis was 0.28 with a standard deviation of 0.24.

The lower and upper bound of the estimated elasticity of land is -0.13 using data from 1984-2008 and 0.55 using data from 1967-1991, respectively. The time-varying elasticity of land indicates an increasing trend from 1961-1986 to 1961-1992. This indicates the land elasticity increases with each additional year of data. Elasticity of land shows a drastically decreasing trend from 1961-1993 to 1961-2008 indicating that with each additional year of data, the land elasticity decrease. In contrast long run time-varying results in table 6 suggest a decreasing but not as drastic as short run time-varying results. This suggests in the over the long and short run the contribution of land to agriculture production has been decreasing.

The mean elasticity of labor from stochastic frontier cumulative rolling regression analysis (table 6) was 0.39 with a standard deviation of 0.05. The lower bound of elasticity of labor is 0.29 and is estimated using data from 1961-1990; the upper bound of labor elasticity is 0.48 estimated using data from 1961-1985. The time-varying elasticity of labor indicates a decreasing trend from 1961-1985 to 1961-1992 followed by increasing trend till 1961-1996 indicating the elasticity decreases and then increase with each additional year of data. Then the labor elasticity measure settles around 0.37. In contrast short run time-varying results in table 5 suggest a decreasing trend and ends up with a labor elasticity measure of 0.014. This suggests in recent years the contribution of labor is not much to agriculture production.

Elasticity of capital indicates the mean from stochastic frontier cumulative rolling regression analysis (table 6) from 1986 to 2008 was 0.08 and a standard deviation of 0.009. The upper and lower bound of the estimated elasticity of capital is 0.098 using data from 1961-1996 and 0.062 using data from 1961-1985. Time-varying elasticity of capital indicates an inverted cup shape trend increasing and then decreasing trend with starting and end capital elasticity measure around 0.06. In contrast short run time-varying results in table 6 suggest a decreasing trend and ends up with a negative sign on the capital.

Long run time-varying fertilizer elasticity was negative and showed a slightly increasing trend over the 24 regression runs. In contrast the short run time-varying fertilizer elasticity was negative from 1961-1985 to 1971-1995 and then became positive with an increase trend to the end with an elasticity of 0.19 suggesting a positive contribution to agriculture production.

Results of elasticity of livestock in table 6 (5) indicates the mean of stochastic frontier cumulative (window) rolling regression analysis from 1986 to 2005 was 0.37 (0.39) with a standard deviation of 0.03 (0.104). Both the short and long run time-varying elasticity of livestock indicates an increasing trend with the short run showing a much higher trend.

With Hicks non-neutral technological changes in inputs short a contrasting trend compared the elasticity of inputs. For example, the elasticity of land and capital showed a decreasing trend in both the short and long run time-varying estimates (figure 1). Hicks non-neutral technological changes in land and capital in figure 2 suggest an increase trend. Similarly the technology associated with fertilizer and livestock showed a decreasing trend. The Hicks neutral technology trend with the short and long run time-varying estimates indicates a decreasing and then an increasing trend.

Finally, returns to scale results indicate the mean of cumulative rolling regression analysis from 1985 to 2008 was 1.21 and a standard deviation of 0.06. However the mean of window rolling regression analysis from 1985 to 2008 was 0.925 and a higher standard deviation of 0.24. Trends in the long run time-varying return to scale indicate a decreasing, increasing and then a decreasing trend. However the short run time-varying returns to scale for Asian countries suggest decreasing trend.

5 Conclusions

In this paper first, the importance of accounting for technical efficiency on the elasticity of inputs, technical change and calculation of returns to scale as defined in proposition 1 is examined. Second, the importance of each additional year of data or information on the elasticity of inputs, technical change estimates and calculation of returns to scale as defined in proposition 2 is quantified applying window and cumulative rolling regression.

Both analyses are conducted using the stochastic frontier analysis of Cobb-Douglas Hicks non-neutral production function with an application to Asian agriculture data from 1961-2008. In contrast to previous studies that assume technical efficient production function, stochastic frontier analysis accounts for technical efficiency and estimates the relationship between input and output quantities via the elasticities and returns to scale. Second, earlier studies assumed elasticity of inputs, technical change and returns to scale to be systematic over time. The time-varying estimates of elasticity of inputs, technical change and returns to scale estimated using window and cumulative rolling regression provide evidence of differential short and long run variation in the elasticity measures.

Estimates from this study indicate returns to scale are underestimated by the traditional panel compared to stochastic frontier model that accounts for inefficiency. These input elasticity are consistent with earlier research but differs with respect to the time period used and use of stochastic frontier analysis. Also, the returns to scale are overestimated by earlier research as they used time-series or pooled that does not account for the spatial variation instead of stochastic frontier panel models that accounts for technical inefficiency.

Short and long run time-varying estimates of elasticity of inputs, technical change and returns to scale indicate differential variations in the short and long run. Further the time-varying elasticity of inputs, technical change and returns to scale indicate variations across inputs and over time questioning the systematic nature due to differential short and long run changes in the agriculture production, investments and domestic and international policies.

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Figure 2: Panel and SFA estimated Short and long run time-varying input elasticity

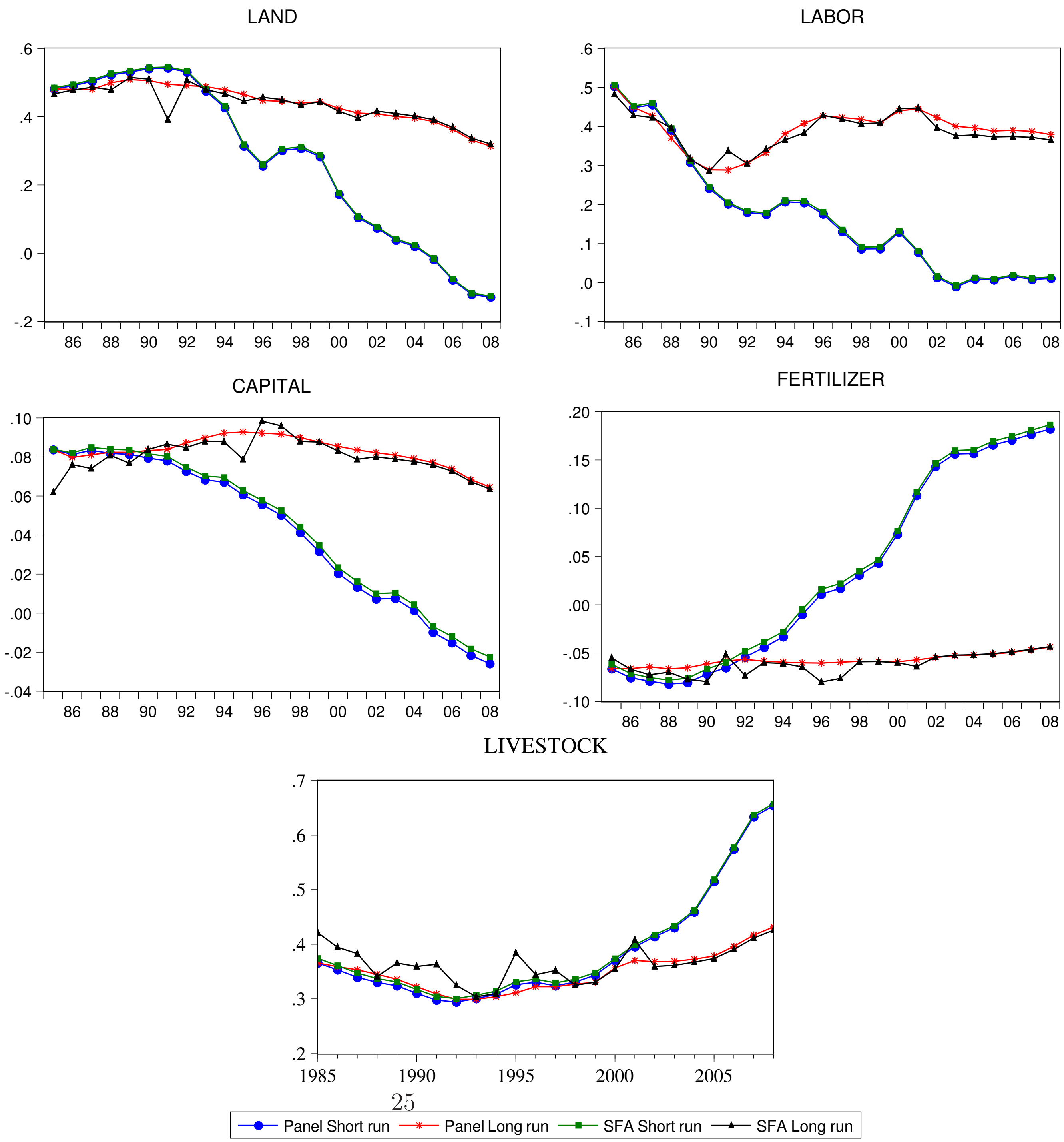

Figure 3: Panel and SFA estimated Short and long run time-varying Hicks non-neutral input elasticity

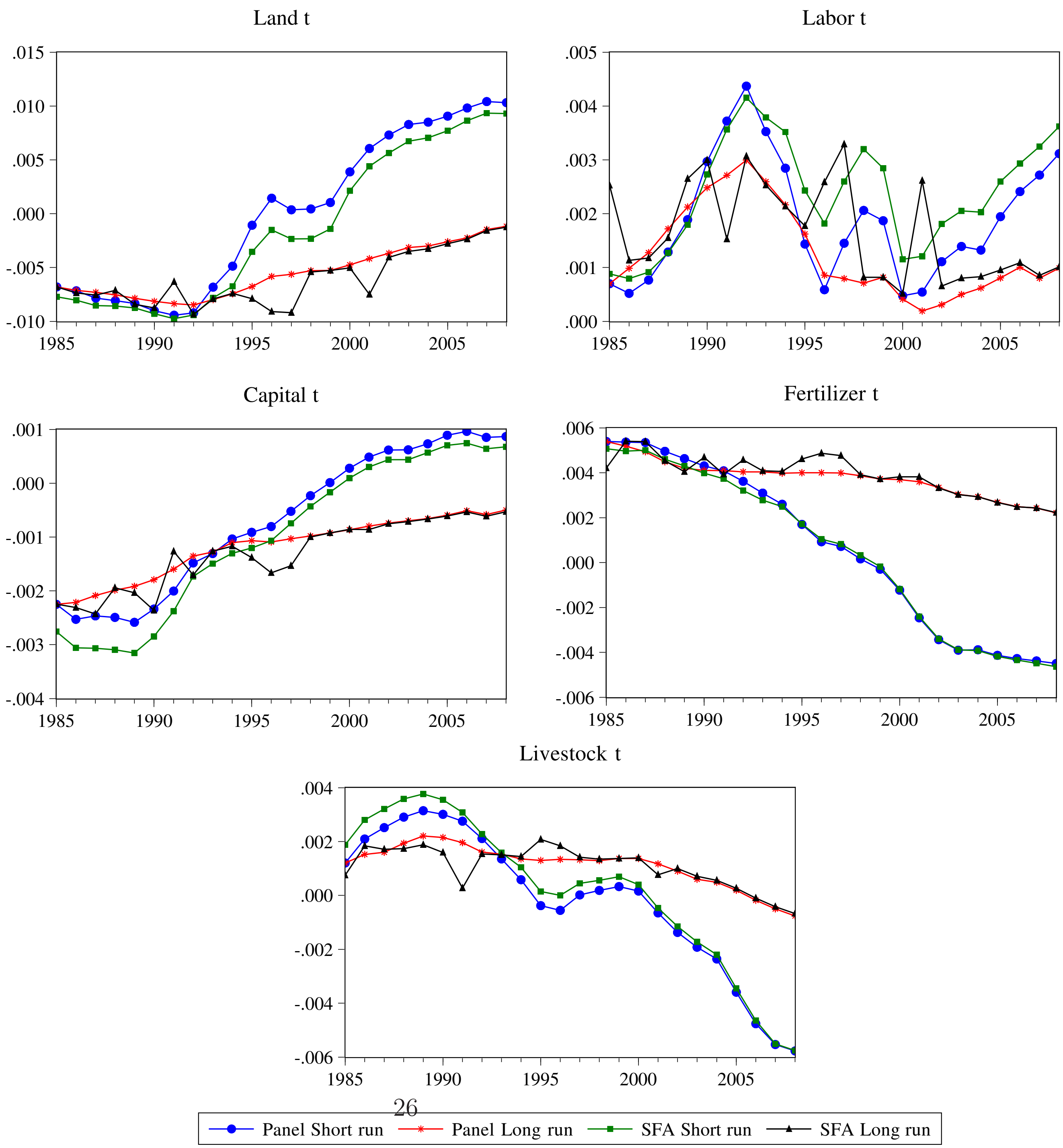

Figure 4: Panel and SFA estimated Short and long run time-varying returns to scale, Hicks neutral and non-neutral technology and total technology

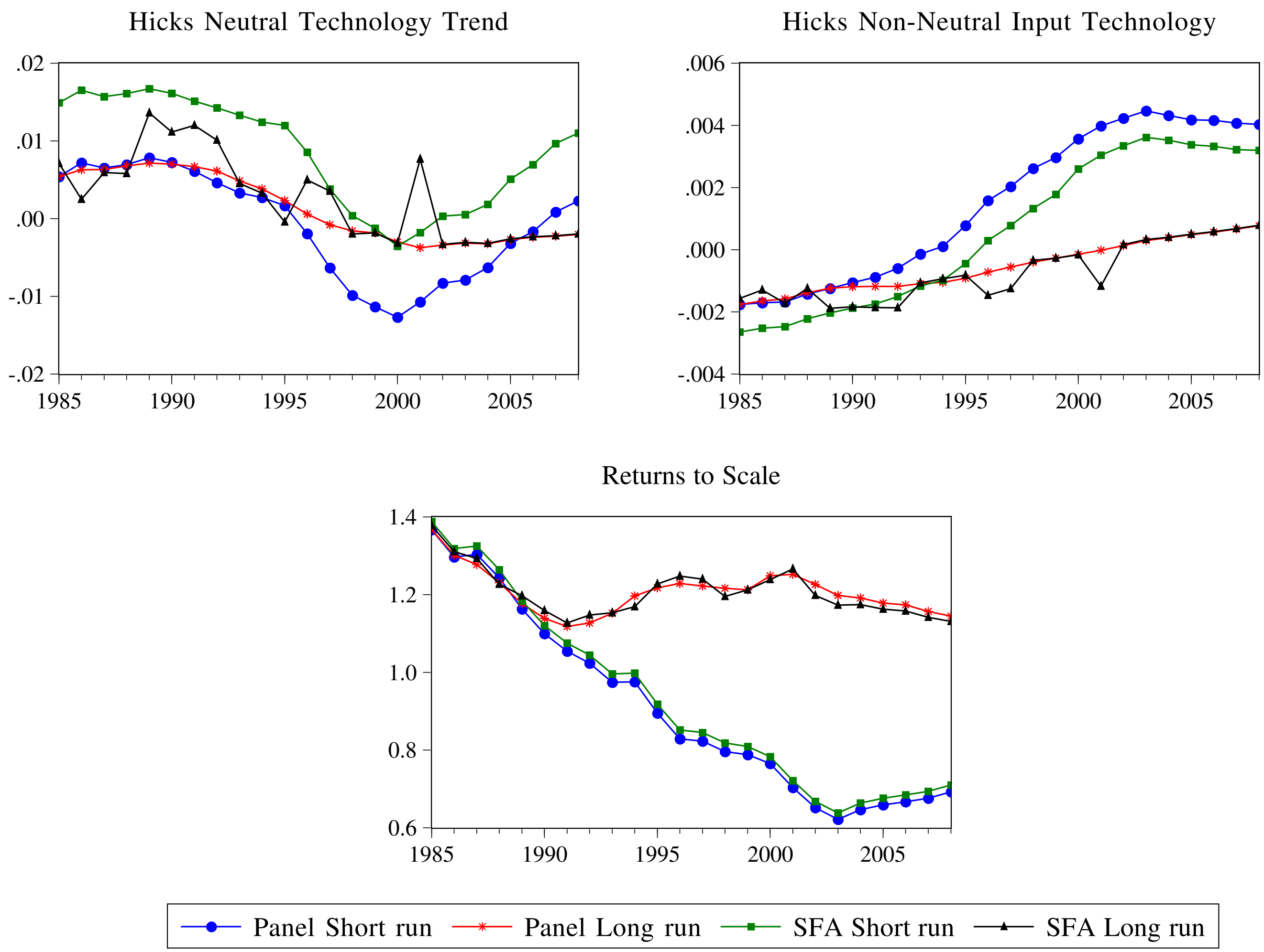

Table 1: Average and standard deviation of variables, 1961-2008

Country	Output	Land	Labor	Capital	Livestock	Fertilizer
			Average			
Bangladesh	72	14,099	29,149	2,015	28,309	682,007
Cambodia	71	2,145	3,076	1,587	3,371	15,686
China	59	171,397	407,401	668,363	243,252	20,953,941
India	68	201,937	191,089	964,473	308,109	9,189,858
Indonesia	69	25,898	36,073	2,798	22,197	1,635,110
Japan	99	4,612	4,923	2,209,005	9,812	1,816,126
Korea, North	87	2,938	3,178	46,945	2,007	437,779
Korea, South	67	2,834	4,316	64,894	3,871	744,354
Lao PDR	60	850	1,406	663	2,347	3,327
Malaysia	63	4,444	1,850	16,361	2,357	712,655
Mongolia	88	433	222	7,021	8,659	6,807
Myanmar	68	11,475	13,562	7,740	12,800	86,312
Nepal	67	3,679	6,434	9,247	10,693	41,518
Pakistan	63	21,792	15,095	181,311	49,467	1,552,561
Philippines	71	13,882	9,933	27,764	9,825	426,057
Singapore	514	5	10	45	188	4,481
Sri Lanka	84	1,996	3,127	15,033	2,656	174,575
Thailand	71	14,292	17,502	175,818	13,429	796,103
Vietnam	58	8,948	20,126	59,575	10,798	811,866
			Standard deviation			
Bangladesh	24	968	5,609	944	3,077	523,578
Cambodia	34	635	923	943	1,131	25,731
China	34	13,192	83,502	456,255	72,361	15,989,617
India	27	13,489	41,872	959,994	33,991	6,968,939
Indonesia	34	6,384	8,570	2,173	8,485	1,185,131
Japan	10	1,303	1,740	1,610,360	1,885	274,762
Korea, North	25	191	274	22,945	539	262,371
Korea, South	25	578	1,746	86,651	1,696	202,336
Lao PDR	34	161	432	376	807	4,153
Malaysia	36	2,558	123	14,986	850	528,442
Mongolia	13	158	23	2,837	1,008	6,584
Myanmar	37	3,412	3,571	3,023	3,478	63,173
Nepal	29	1,009	2,154	11,048	2,031	34,785
Pakistan	31	3,516	4,287	150,050	16,925	1,179,548
Philippines	28	2,269	2,337	23,028	1,531	244,385
Singapore	343	5	6	22	101	2,289
Sri Lanka	17	158	516	3,993	521	69,936
Thailand	28	2,714	3,113	274,174	1,467	722,518
Vietnam	36	2,186	5,427	59,309	3,819	781,476

Units of output is gross PIN (1999-2001=100); land is 1000 hectares; labor in 1000s; capital and livestock in numbers and fertilizer in metric tons.

Table 2: Average and standard deviation of parameter coefficients or elasticity of inputs of production function for short and long-run regressions

	Panel Model				**SFA Model**			
	Short run		**Long run**		**Short run**		**Long run**	
	Mean	**Stdev**	**Mean**	**Stdev**	**Mean**	**Stdev**	**Mean**	**Stdev**
Intercept	-5.1284	1.9173	-7.6283	0.525	-5.1272	1.9168	-7.5154	0.5512
Land	0.2735	0.2353	0.4409	0.0552	0.2775	0.2354	0.4359	0.0525
Labor	0.1687	0.1556	0.3914	0.0533	0.1727	0.1558	0.3856	0.0472
Capital	0.0413	0.0383	0.0831	0.0072	0.0438	0.0377	0.0803	0.0089
Livestock	0.3885	0.1052	0.3486	0.036	0.3938	0.1041	0.3648	0.0334
Fertilizer	0.0323	0.1004	-0.0577	0.0061	0.0368	0.0998	-0.0615	0.0109
Land*t	-0.0001	0.0074	-0.0055	0.0023	-0.0015	0.0071	-0.0061	0.0025
Labor*t	0.0019	0.0011	0.0013	0.0008	0.0024	0.001	0.0017	0.0009
Capital*t	-0.0007	0.0013	-0.0012	0.0006	-0.001	0.0015	-0.0013	0.0006
Livestock*t	-0.0002	0.0027	0.0011	0.0008	0.0002	0.0028	0.0011	0.0008
Fertilizer*t	0.0006	0.0037	0.0038	0.0008	0.0005	0.0036	0.0039	0.0009
HN trend	-0.0007	0.0069	0.0014	0.0043	0.0085	0.0069	0.0027	0.0055
HNN trend	0.0015	0.0024	-0.0005	0.0008	0.0006	0.0024	-0.0007	0.0009
HNN & HN	0.0008	0.0093	0.0008	0.0051	0.0091	0.0093	0.002	0.0064
Returns to Scale	0.9044	0.2392	1.2062	0.0578	0.9246	0.2406	1.2051	0.0622

Table 3: Ratio of SFA over panel Short run time-varying elasticity of inputs and returns to scale

roll	Land	Labor	Capital	Livestock	Fertilizer	Land*t	Labor*t	Capital*t	Lstock*t	Fert*t	HN	RTS
1961-1985	101%	101%	100%	102%	93%	113%	126%	123%	157%	94%	275%	102%
1962-1986	101%	101%	101%	102%	94%	112%	153%	121%	133%	93%	230%	102%
1963-1987	101%	101%	102%	102%	95%	109%	119%	125%	128%	94%	241%	102%
1964-1988	101%	101%	102%	102%	95%	106%	99%	124%	123%	93%	232%	102%
1965-1989	101%	101%	103%	102%	94%	105%	95%	122%	120%	93%	213%	102%
1966-1990	101%	101%	103%	102%	93%	103%	92%	122%	118%	92%	223%	102%
1967-1991	101%	102%	103%	102%	92%	103%	96%	119%	112%	91%	248%	102%
1968-1992	101%	102%	103%	102%	89%	102%	95%	117%	108%	88%	310%	102%
1969-1993	101%	102%	103%	102%	87%	115%	107%	114%	117%	90%	404%	102%
1970-1994	101%	102%	104%	102%	84%	138%	124%	126%	179%	96%	458%	102%
1971-1995	102%	102%	104%	102%	47%	332%	170%	132%	-39%	101%	722%	103%
1972-1996	102%	103%	104%	102%	147%	-105%	309%	132%	-1%	112%	-435%	103%
1973-1997	102%	104%	105%	102%	130%	-637%	179%	143%	2102%	116%	-60%	103%
1974-1998	102%	106%	107%	102%	114%	-540%	155%	184%	298%	199%	-4%	103%
1975-1999	102%	105%	110%	101%	109%	-135%	152%	-1336%	214%	62%	11%	103%
1976-2000	102%	103%	115%	101%	105%	55%	243%	35%	246%	96%	28%	102%
1977-2001	104%	105%	122%	101%	103%	73%	223%	62%	71%	98%	17%	102%
1978-2002	105%	128%	140%	101%	102%	77%	163%	71%	84%	99%	-4%	103%
1979-2003	110%	68%	139%	101%	102%	81%	148%	70%	90%	99%	-6%	103%
1980-2004	117%	136%	311%	101%	102%	83%	153%	78%	93%	101%	-29%	103%
1981-2005	81%	150%	69%	101%	102%	85%	134%	79%	96%	101%	-158%	103%
1982-2006	96%	122%	78%	101%	102%	88%	122%	77%	98%	102%	-411%	103%
1983-2007	97%	145%	84%	101%	102%	90%	119%	75%	100%	102%	1162%	103%
1984-2008	97%	132%	87%	101%	102%	90%	116%	78%	100%	103%	485%	103%

Table 4: Ratio of SFA over panel Long run time-varying elasticity of inputs and returns to scale

roll	Land	Labor	Capital	Livestock	Fertilizer	Land*t	Labor*t	Capital*t	Lstock*t	Fert*t	HNtrend	RTS
1961 - 1985	97%	96%	74%	115%	83%	100%	361%	100%	62%	78%	131%	101%
1961 - 1986	100%	95%	95%	110%	101%	104%	115%	104%	121%	104%	40%	101%
1961 - 1987	101%	99%	91%	108%	113%	104%	92%	116%	107%	109%	94%	101%
1961 - 1988	96%	107%	98%	99%	105%	95%	90%	98%	90%	101%	85%	100%
1961 - 1989	101%	101%	93%	109%	118%	107%	125%	106%	85%	96%	191%	102%
1961 - 1990	101%	99%	101%	111%	130%	108%	121%	132%	74%	114%	159%	102%
1961 - 1991	79%	117%	103%	118%	88%	76%	56%	79%	14%	96%	179%	101%
1961 - 1992	103%	100%	97%	108%	129%	110%	102%	126%	96%	113%	165%	102%
1961 - 1993	98%	103%	98%	101%	103%	99%	98%	99%	99%	101%	93%	100%
1961 - 1994	98%	96%	95%	102%	102%	99%	99%	106%	107%	102%	86%	98%
1961 - 1995	96%	94%	85%	123%	107%	117%	110%	129%	160%	115%	-19%	101%
1961 - 1996	102%	100%	107%	107%	132%	156%	301%	153%	138%	122%	867%	102%
1961 - 1997	101%	99%	105%	109%	128%	163%	413%	149%	107%	119%	-437%	101%
1961 - 1998	99%	97%	98%	99%	101%	102%	115%	102%	104%	101%	124%	98%
1961 - 1999	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
1961 - 2000	98%	101%	97%	99%	102%	106%	125%	99%	102%	103%	104%	99%
1961 - 2001	96%	101%	94%	110%	112%	180%	1354%	108%	65%	106%	-204%	101%
1961 - 2002	102%	94%	97%	98%	99%	110%	211%	102%	111%	100%	97%	98%
1961 - 2003	102%	94%	97%	98%	99%	111%	160%	102%	118%	100%	97%	98%
1961 - 2004	102%	96%	98%	99%	99%	109%	134%	101%	115%	100%	98%	99%
1961 - 2005	101%	96%	98%	99%	99%	107%	118%	102%	134%	100%	97%	99%
1961 - 2006	102%	96%	98%	99%	99%	105%	108%	105%	58%	100%	97%	99%
1961 - 2007	102%	96%	98%	99%	99%	106%	106%	105%	84%	100%	98%	99%
1961 - 2008	102%	96%	98%	99%	99%	107%	103%	106%	89%	100%	98%	99%

Table 5: Short run time-varying elasticity of inputs and returns to scale from stochastic frontier regressions

Year	Land	Labor	Capital	Livestock	Fertilizer	HN	HNN	RTS
1961 - 1985	**0.485**	**0.507**	**0.084**	**0.374**	**-0.062**	**0.0149**	**-0.0027**	**1.388**
1962 - 1986	**0.494**	**0.452**	**0.082**	**0.361**	**-0.071**	**0.0165**	**-0.0025**	**1.318**
1963 - 1987	**0.508**	**0.46**	**0.085**	**0.347**	**-0.075**	**0.0157**	**-0.0025**	**1.325**
1964 - 1988	**0.526**	**0.395**	**0.084**	**0.337**	**-0.078**	**0.0161**	**-0.0022**	**1.264**
1965 - 1989	**0.534**	**0.312**	**0.084**	**0.331**	**-0.076**	**0.0167**	**-0.002**	**1.184**
1966 - 1990	**0.544**	**0.245**	**0.082**	**0.317**	**-0.067**	**0.0161**	**-0.0019**	**1.121**
1967 - 1991	**0.545**	**0.205**	**0.08**	**0.304**	**-0.06**	**0.0151**	**-0.0017**	**1.075**
1968 - 1992	**0.534**	**0.183**	**0.075**	**0.301**	**-0.048**	**0.0142**	**-0.0015**	**1.044**
1969 - 1993	0.479	0.178	0.07	**0.307**	**-0.038**	0.0133	-0.0012	**0.996**
1970 - 1994	0.431	0.211	0.069	**0.314**	**-0.028**	0.0124	-0.001	**0.998**
1971 - 1995	0.319	0.209	0.063	**0.331**	**-0.005**	0.012	-0.0004	**0.918**
1972 - 1996	0.261	0.181	0.058	**0.336**	**0.016**	0.0086	0.0003	**0.851**
1973 - 1997	0.306	0.135	0.052	**0.329**	**0.022**	0.0038	0.0008	**0.845**
1974 - 1998	**0.312**	**0.091**	0.044	**0.336**	**0.035**	0.0004	0.0013	**0.818**
1975 - 1999	**0.287**	**0.091**	0.035	**0.348**	**0.047**	-0.0013	0.0018	**0.809**
1976 - 2000	**0.176**	**0.133**	0.023	**0.374**	**0.077**	-0.0036	0.0026	**0.783**
1977 - 2001	**0.108**	**0.081**	0.016	**0.399**	**0.117**	-0.0018	0.003	**0.721**
1978 - 2002	0.078	0.016	**0.01**	**0.418**	**0.147**	0.0003	0.0033	**0.668**
1979 - 2003	0.042	-0.008	**0.01**	**0.433**	**0.16**	0.0005	0.0036	**0.638**
1980 - 2004	0.024	0.013	**0.004**	**0.462**	**0.161**	0.0018	0.0035	**0.663**
1981 - 2005	-0.015	0.01	**-0.007**	**0.518**	**0.169**	0.0051	0.0034	**0.676**
1982 - 2006	**-0.075**	**0.019**	**-0.012**	**0.578**	**0.174**	**0.0069**	**0.0033**	**0.684**
1983 - 2007	**-0.117**	**0.011**	**-0.018**	**0.637**	**0.181**	**0.0096**	**0.0032**	**0.693**
1984 - 2008	**-0.126**	**0.014**	**-0.022**	**0.658**	**0.186**	**0.011**	**0.0032**	**0.71**
Mean	0.277	0.173	0.044	0.394	0.037	0.009	0.001	0.925
Std	0.235	0.156	0.038	0.104	0.1	0.007	0.002	0.241
Minimum	-0.126	-0.008	-0.022	0.301	-0.078	-0.004	-0.003	0.638
Maximum	0.545	0.507	0.085	0.658	0.186	0.017	0.004	1.388

Table 6: Long run time-varying elasticity of inputs and returns to scale from stochastic frontier regressions

Year	Land	Labor	Capital	Livestock	Fertilizer	HN	HNN	RTS
1961 - 1985	**0.467**	**0.483**	**0.062**	**0.421**	**-0.055**	**0.0071**	**-0.0016**	**1.378**
1961 - 1986	**0.478**	**0.429**	**0.076**	**0.395**	**-0.067**	**0.0025**	**-0.0013**	**1.31**
1961 - 1987	**0.486**	**0.423**	**0.074**	**0.383**	**-0.073**	**0.0059**	**-0.0017**	**1.293**
1961 - 1988	**0.478**	**0.396**	**0.081**	**0.341**	**-0.07**	**0.0058**	**-0.0012**	**1.227**
1961 - 1989	**0.515**	**0.317**	**0.077**	**0.366**	**-0.077**	**0.0136**	**-0.0019**	**1.197**
1961 - 1990	**0.51**	**0.285**	**0.084**	**0.36**	**-0.08**	**0.0111**	**-0.0018**	**1.159**
1961 - 1991	**0.391**	**0.337**	**0.086**	**0.364**	**-0.051**	**0.012**	**-0.0019**	**1.127**
1961 - 1992	**0.507**	**0.304**	**0.085**	**0.325**	**-0.073**	**0.0101**	**-0.0019**	**1.147**
1961 - 1993	**0.479**	**0.342**	**0.088**	**0.304**	**-0.06**	**0.0045**	**-0.0011**	**1.153**
1961 - 1994	**0.467**	**0.365**	**0.088**	**0.309**	**-0.061**	**0.0033**	**-0.0009**	**1.169**
1961 - 1995	**0.445**	**0.383**	**0.079**	**0.384**	**-0.064**	**-0.0004**	**-0.0008**	**1.227**
1961 - 1996	**0.457**	**0.429**	**0.098**	**0.344**	**-0.08**	**0.005**	**-0.0015**	**1.248**
1961 - 1997	**0.45**	**0.418**	**0.096**	**0.352**	**-0.076**	**0.0035**	**-0.0013**	**1.24**
1961 - 1998	**0.434**	**0.407**	**0.088**	**0.325**	**-0.059**	**-0.002**	**-0.0003**	**1.195**
1961 - 1999	**0.444**	**0.409**	**0.088**	**0.331**	**-0.059**	**-0.0019**	**-0.0003**	**1.212**
1961 - 2000	**0.415**	**0.445**	**0.083**	**0.355**	**-0.06**	**-0.0032**	**-0.0002**	**1.239**
1961 - 2001	**0.396**	**0.447**	**0.079**	**0.408**	**-0.064**	**0.0076**	**-0.0012**	**1.266**
1961 - 2002	**0.416**	**0.396**	**0.08**	**0.36**	**-0.054**	**-0.0033**	**0.0002**	**1.197**
1961 - 2003	**0.409**	**0.376**	**0.079**	**0.361**	**-0.052**	**-0.0031**	**0.0003**	**1.173**
1961 - 2004	**0.402**	**0.379**	**0.078**	**0.367**	**-0.052**	**-0.0032**	**0.0004**	**1.174**
1961 - 2005	**0.391**	**0.373**	**0.076**	**0.374**	**-0.051**	**-0.0026**	**0.0005**	**1.163**
1961 - 2006	**0.369**	**0.374**	**0.073**	**0.391**	**-0.049**	**-0.0023**	**0.0006**	**1.157**
1961 - 2007	**0.337**	**0.372**	**0.067**	**0.411**	**-0.046**	**-0.0022**	**0.0007**	**1.141**
1961 - 2008	**0.32**	**0.365**	**0.064**	**0.426**	**-0.043**	**-0.002**	**0.0008**	**1.131**
Mean	0.436	0.386	0.08	0.365	-0.061	0.003	-0.001	1.205
Std	0.053	0.047	0.009	0.033	0.011	0.005	0.001	0.062
Minimum	0.32	0.285	0.062	0.304	-0.08	-0.003	-0.002	1.127
Maximum	0.515	0.483	0.098	0.426	-0.043	0.014	0.001	1.378