Agribusiness and Applied Economics Report No. 635 October 2008

Accounting for (In)Efficiency in the Estimation of Time-Varying Returns to Scale

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Acknowledgments

Thanks are extended to our colleagues David Saxowsky and Robert Hearne for reviewing this manuscript and to Edie Watts for document preparation.

Copies of this publication are available electronically at the following website: http://agecon.lib.umn.edu/. Please address your inquiries regarding this publication to the Department of Agribusiness and Applied Economics, North Dakota State University Dept 7610, PO Box 6050, Fargo, ND 58108-6050, phone (701-231-7441), fax (701-231-7400), or e-mail: ndsu.agribusiness@ndsu.edu.

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Abstract

This paper has a two-fold contribution. First, it examines the importance of accounting for (in)efficiency in the estimation of primal production function on the input elasticities, technical change, and calculation of returns to scale. Second, it applies a variant of the rolling regression technique to identify time-varying input elasticities, technical change, and return to scale. Empirical application to the Asian agriculture sector using Food and Agricultural Organization data from 1961-2005 indicates returns to scale are underestimated by the traditional pooled and panel models. Further, the time-varying estimates of input elasticities, technical change, and returns to scale indicate variations with each additional year of information.

JEL classification:

Keywords: *Asian agriculture sector, time-varying input elasticities, technical change, and returns to scale, pooled, two-way random effect, stochastic frontier analysis, 1961-2005.*

Accounting for (In)Efficiency in the Estimation of Time-Varying Returns to Scale[1]

Saleem Shaik

I. 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 elasticity of inputs and outputs, and compute returns to scale for a firm, industry, sector, state, or country. Overall, the contributions of the neoclassical economists have led to the development of theory and new empirical methods which often demand new data that are constantly being designed to use theory to test a particular problem applied to economies of all stages of development.

Much of the past 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. The underlying outcome of this effort on production functions is the identification, estimation, and examination of elasticity of inputs, technical change, and returns to scale. Production functions have not been as thoroughly measured as well as it has in developed nations. However, when estimating production function in developing countries, accounting for inefficiency is critical, particularly when accessing the impact of the green revolution.

There are several reasons for identification, estimation, and examination of input elasticities, technical change, and returns to scale accounting for inefficiency. First, technical experimental station data, where crops are allowed to grow under ideal conditions, are often overused when evaluating the potential of the agricultural sector. What was (is) badly needed is information on the gap between crops grown under ideal conditions and performance in the field. Accounting for efficiency may provide a better understanding on the size of this gap. Second, while developing nations have greatly benefited from "research" and product development, they often lack adequate extension services. This skewing of international and domestic spending towards research and experiment stations and away from extension makes it quite likely the inefficiencies will occur when new technology is brought to the field. Third, much of the "new" technology (seed, equipment, etc) has been imported from countries or regions with specific soil and weather conditions. For example, seed developed at the International Rice Research Institute in the Philippines may not perform ideally when transferred to other countries, perhaps Bangladesh. At the disaggregate level, this information would be useful for farmers, regional officials, rural banks, and input suppliers as to the input variables driving output and ultimately

[1] This paper has benefited from discussions with and suggestions of Carlos Arnade at USDA, ERS, and David Saxowsky and Robert Hearne from North Dakota State University. Any remaining errors are my own.

their profitability. At the aggregate level, it is useful for policy makers as it will provide information on future investments on technology innovations of inputs to improve output and profitability for overall growth of the economy.

The interaction between economist Paul Douglas and mathematician Charles W. Cobb resulted in the famous two-factor Cobb-Douglas production function, $y = b\,L^{K} C^{1-K}$. The exponents constitute the elasticity of labor (L), capital (C) and if the exponents sum to one, exhibits constant returns to scale. Existing literature estimating primal production functions have computed the input elasticities and reported the returns to scale using aggregate and disaggregate data (Mundlak, Larson, and Butzer, 1997; Basu and Fernald, 1997; Trueblood, 1991) without accounting for inefficiency. When the production function allows for technological change, it results in the Solow growth equation, $y = e^{rt} L^{K} C^{1-K}$ (Solow, 1957). The residual term e^{rt} captures the trend in technical change over time. In the post-World War II era, the focus of technology change was analyses of cross-country differences in agricultural productivity measures using parametric methods (Heady, 1944; Heady and Dillon, 1961; Hayami, 1969 and 1970; Hayami and Ruttan, 1970 and 1971; Kawagoe and Hayami, 1983 and 1985; and Kawagoe, Hayami, and Ruttan, 1985), linear programming methods accounting for technical efficiency and technical changes (Bureau, Fare, and Grosskopf, 1995; Arnade, 1998; and Nin, Arndt, and Preckel, 2003), and stochastic frontier analysis.

Comprehensive literature reviews (Forsund, Lovell, and Schmidt, 1980; Schmidt, 1986; Bauer, 1990; Greene, 1993; and Kumbhakar and Lovell, 2000) on the use of stochastic frontier analysis has been evolving since it was first proposed by Aigner, Lovell, and Schmidt; Meeusen and van den Broeck in the same year, 1977. The 1990s produced a surge in the application of the stochastic frontier analysis to measure technical change, efficiency change, and productivity change. Furthermore within the primal framework, progress has been made on incorporating multiple outputs and inputs via the distance functions (for discussions see Fare, Grosskopf, and Lovell), adjusting for time series properties, correcting for autocorrelation and heteroskedasticity, and finally using Bayesian techniques in the parametric efficiency measures. Additionally, research has investigated the influence of a broader set of determinants of inefficiency, namely policy, political, geographic variables, market structure conduct and performance hypothesis, farm size, farm programs, and finally heterogeneity.

This research first examines the importance of accounting for (in)efficiency in the estimation of input elasticities, technical change, and calculation of returns to scale using the stochastic frontier estimation of primal production function. Stochastic frontier estimation has become a popular tool to model the production relationship between input and output quantities and has been primarily used to estimate the efficiency[2] of firms, states, and countries. Traditional estimation of input elasticities[3], technical change, and returns to scale does not account for inefficiency in the estimation of production function.

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[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] 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.

Stochastic frontier analysis accounts for inefficiency in the estimation of input elasticities, technical change, and calculation of returns to scale. Is it necessary to account for inefficiency in the estimation of input elasticities, technical change, and returns to scale? The answer is yes, for the simple reason that the estimation of elasticity and return to scale should be based on the relationship between the actual inputs used and final output. Accounting for inefficiency which was not done in production function estimation prior to the 1980s, leads to realization of true input elasticities, technical change, and returns to scale measures. If inefficiency is not accounted, it is possible to over or under estimate input elasticity. For example, in countries dominated by nonfarm economy, an increase in the education level leads to labor saving technology due to increased productivity. Thus, the elasticity of labor is expected to be lower if inefficiency is accounted for in the stochastic frontier estimation compared to the pooled or random effect models. In countries dominated by farm economy, labor elasticity is expected to be higher due to the availability and extensive use of labor. For inputs like fertilizer, the elasticities might be lower in the stochastic frontier estimation compared to the pooled or random effect models. This could be possible if the use of fertilizer was relatively high but used inefficiently. Hence, accounting for inefficiency in the production function would lead to true input elasticities, technical change, and returns to scale. Accounting for inefficiency also quantifies the gap between crops grown in ideal conditions (technical experimental station data), performance in the field, and across countries due to transfer of "new" technology (seed, equipment etc).

Second, literature in this area seldom estimates the importance of time-varying input elasticities, technical change, 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 stock's sensitivity to the market and identify variations in stock prices. In the context of production function, input elasticities, technical change, and returns to scale were assumed to be systematic (constant over time) and driven by state, national, and worldwide difference. However, the systematic nature of the input elasticities, technical change, and returns to scale is questionable due to changes in the industry induced by the advancements in structure of agriculture production and domestic and international policies. This paper aims to close this gap by empirically analyzing the time-varying estimates of input elasticities, technical change, and returns to scale. Cumulative rolling regression, a variant of the rolling regression technique is applied to estimate time-varying input elasticity and returns to scale. The cumulative rolling regression allows the quantification of changes in the input elasticities, technical change, and returns to scale estimates with each additional year of data or information.

Next, the time-varying stochastic production function frontier model is proposed along with the traditional pooled and panel model of production function. 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 15 Asian countries forming the cross-sectional units over the period 1961-2005 with emphasis on the agricultural sector are presented next. Finally, general and policy implications are presented.

II. Time-Varying 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 panel data. To estimate input elasticity, technical change, and compute returns to scale of a country i, $i = 1,\ldots,I$ over time t, $t = 1,\ldots,T$, the basic form of the production function can be represented as:

(1) $$y_{i,t} = f\left(\left(x_{i,t};\beta\right),t\right)\cdot\varepsilon_{i,t}$$

where y denotes output produced from a vector of input, x, β the associated vector of parameter coefficients, t the time trend represents the technical change, and ε the error term. These parameter coefficients are the elasticity of inputs if the vectors of inputs and output are in logarithmic form. This research focuses on the pooled and the two-way random effects specification of the initial production function model.

The two-way random effects model allows the error, $\varepsilon_{i,t}$ to be decomposed into spatial, u_i temporal, v_t and remaining residual, $w_{i,t}$ components. This can be represented as

(2) $$y_{i,t} = f\left(\left(x_{i,t};\beta\right),t\right)\cdot\left(u_i + v_t + w_{i,t}\right)$$

where u represents a $1 \times I$ matrix of spatial random error, v represents a $1 \times T$ matrix of temporal random error, and w represents a $1 \times NT$ matrix of remaining random error assumed to be uncorrelated and follow normal distribution.

Following Battese and Coelli, 1992, the error component stochastic frontier production function that decomposes the error term, ε into random error, v and u efficiency is used in the estimation. This can be represented for panel data as:

(3) $$y_{i,t} = f\left(\left(x_{i,t};\beta_{sfa}\right),t\right)\cdot v_{i,t} - u_{i,t}$$

where β_{sfa} is the vector of error component stochastic frontier parameter coefficients, $v_{i,t}$ 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 $u_{i,t}$ represents technical efficiency. This variable must be positive and is an absolutely normally distributed variable with mean zero and variance σ_U^2. The variables y and x are as defined in equation (1). The returns to scale are computed as the sum of the parameter coefficients or the elasticity of inputs.

To examine time-varying input elasticities, technical change, 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 and Bayesian techniques have been used in the literature. These are far more costly ways to examine the importance of each additional year of information on the efficiency or coefficient estimates. To examine time-varying input elasticities, technical change, and the returns to scale, a cumulative rolling regression of stochastic production function frontier is estimated. With cumulative rolling regression, a set of coefficients are estimated with each additional year of data. To represent the primal production function in the cumulative rolling stochastic frontier analysis framework, equation (3) can be re-written as:

(4) $$y^{j}_{i,t} = f\left(\left(x^{j}_{i,t};\beta^{j}\right),t^{j}\right)\cdot v^{j}_{i,t} - u^{j}_{i,t}$$

where $j = 26,.......,T$ and represents the number of rolling 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.

Proposition 1: *Comparison of pool/panel models and stochastic frontier model allows the difference (over or under estimation) in input elasticity and return to scale associated with accounting for inefficiency in the estimation of production function to be quantified.*

Conceptually, over or under estimation of input elasticity and return to scale associated with accounting for inefficiency[4] using stochastic frontier analysis could be quantified by comparing the parameters estimated from pool or panel and stochastic frontier model. Earlier literature have examined one or the other methods and compared the differences between methods. Comparison of stochastic frontier model and pool or panel model would be useful because this gap is important as it relates to issues such as adoption and transfer of appropriate technology to the farm and across countries. Over or under estimation of input elasticity can be represented as:

(5) $$\beta_{sfa} \text{ ¦ } \beta = \frac{\partial y}{\partial x} \text{ ¦ } \frac{\partial y}{\partial\left(x + x_{ineff}\right)} \equiv \frac{\partial y}{\partial x} \text{ ¦ } \frac{\partial y}{\partial x} \pm \frac{\partial y}{\partial x_{ineff}}$$

where β_{sfa} and β are the parameter coefficients estimated from stochastic frontier model and pool or 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 pool or panel model would be underestimated compared to β_{sfa} estimated from stochastic frontier model *if and only if (iff)* the inputs are actually utilized in the production even after accounting for inefficiency. The pool or 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. The β_{sfa} will be equal to β *iff* the same amount of

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[4] 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.

inputs are utilized with and without accounting for inefficiency in the production function. The over or under estimation of parameter $\left(\beta_{sfa}-\beta\right)$ can be represented as:

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

Proposition 2: Time-varying parameter, β^{j} estimated from the equation (4) allows quantifying the extent of variation in the parameter with each additional year of information.

Irrespective of the model (pool, panel or stochastic frontier), the parameter estimate varies with each additional year and this variation would be captured if the input and output variation is different than the earlier sample. Mathematically this can be represented as

$$
(7) \qquad \beta^{j+1} \text{¦} \ \beta^{j} = \frac{\partial y^{j+1}}{\partial x^{j+1}} \text{¦} \ \frac{\partial y^{j}}{\partial x^{j}} \equiv \frac{\partial\left(y^{j}+y^{1}\right)}{\partial\left(x^{j}+x^{1}\right)} \text{¦} \ \frac{\partial y^{j}}{\partial x^{j}}
$$

The β^{j+1} estimated from production function with j observations plus one additional year of observation would be greater than β estimated with j observations if the marginal effect, $\beta^{1}=\partial y^{1}/\partial x^{1}$ is positive and greater than $\beta^{j}=\partial y^{j}/\partial x^{j}$. The β^{j+1} parameter estimated from production function with j observations plus one additional year of observation would be less than β parameter estimated with j observations if the marginal effect, $\beta^{1}=\partial y^{1}/\partial x^{1}$ is negative and greater than $\beta^{j}=\partial y^{j}/\partial x^{j}$. The β^{j+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

$$
8) \qquad \beta^{j+1}-\beta^{j} \Rightarrow \left\{ \begin{array}{llll} positive & \left(\frac{\partial y^{j}}{\partial x^{j}}+\frac{\partial y^{1}}{\partial x^{1}}\right) & or\ \left(\beta^{j}+\beta^{1}\right) & ...iff\ \beta^{1}\ is\ positive \\ zero & \left(\frac{\partial y^{j}}{\partial x^{j}}+0\right) & or\ \left(\beta^{j}+0\right) & ...iff\ \beta^{1}\ is\ zero \\ negative & \left(\frac{\partial y^{j}}{\partial x^{j}}-\frac{\partial y^{1}}{\partial x^{1}}\right) & or\ \left(\beta^{j}-\beta^{1}\right) & ...iff\ \beta^{1}\ is\ negative \\ & & & \&\ greater\ than\ \beta^{1} \end{array} \right\}
$$

The over or under estimation in input elasticity $\left(\beta_{sfa} - \beta\right)$ 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.

III. Input and Output Agriculture Sector Data for Asian Countries

This study is based on Food and Agricultural Organization data available online. The study includes 15 Asian countries for the period 1961 to 2005. For the output and the five inputs, a quantity index with 1961 as the base year was constructed.

Output Series

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 aggregate output variable are available on the FAO webpage, www.fao.org.

Input Series

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 (Rao and Coelli, 2003). 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 (P_2O_2), and phosphate (K_2O) 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 buffalo, cattle, goats, pigs, and sheep. The number of 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. Average and Standard Deviations of Variables, 1961-2005

Country	Output	Land	Labor	Capital	Fertilizer	Livestock
			Average			
Bangladesh	152.18	121.58	178.20	512.79	2,862.11	138.82
Cambodia	115.37	80.97	158.56	227.89	144.65	266.40
China	286.48	106.75	153.39	1,106.20	2,575.88	897.07
India	186.73	110.93	166.88	2,554.29	2,431.97	150.94
Indonesia	241.75	142.28	164.02	1,490.80	1,101.64	183.04
Malaysia	332.64	185.59	188.60	1,174.61	871.29	193.86
Myanmar	218.15	140.33	149.76	696.35	1,484.64	177.04
North Korea	190.64	116.25	160.47	836.84	379.22	210.81
Nepal	179.26	153.28	167.32	1,689.96	29,797	189.13
Pakistan	254.67	138.92	199.80	2,857.11	3,427.76	192.77
Philippines	215.39	140.74	191.04	227.82	508.62	216.89
South Korea	243.00	90.32	150.41	220,201	231.02	412.63
Sri Lanka	159.39	122.01	153.30	204.51	156.38	111.23
Thailand	240.57	177.99	167.80	748.18	4,511.56	173.55
Vietnam	217.86	139.66	168.85	4,235.85	394.10	212.15
All Countries	**215.60**	**131.17**	**167.89**	**1,325.94**	**3,391.85**	**248.42**
			Standard deviation			
Bangladesh	42.56	8.93	53.37	231.16	2,214.90	30.45
Cambodia	44.37	21.74	47.16	84.30	126.60	143.83
China	162.97	6.15	29.69	687.74	1,928.00	711.46
India	71.68	5.82	46.13	2,458.04	1,802.46	45.66
Indonesia	114.04	30.37	40.21	1,652.75	791.87	73.05
Malaysia	178.85	54.34	62.36	1,042.18	621.68	74.79
Myanmar	98.98	33.14	30.34	426.17	1,197.68	42.17
North Korea	54.81	8.02	34.36	611.62	204.12	69.30
Nepal	68.63	38.13	50.03	1,190.41	25,981	53.37
Pakistan	121.69	22.18	74.68	2,320.40	2,612.60	61.78
Philippines	76.58	20.16	60.78	62.10	286.86	84.12
South Korea	87.16	16.56	26.35	313,751	63.97	251.36
Sri Lanka	31.30	9.80	29.03	60.26	44.18	10.54
Thailand	90.91	38.88	36.94	780.63	4,163.68	44.74
Vietnam	124.16	35.52	45.13	6,086.94	458.71	115.28
All Countries	**91.25**	**23.32**	**44.44**	**1,263.91**	**2,833.25**	**120.79**

Table 1 provides the means and standard deviations of the output and input index variables used in the analysis for the period 1961-2005. Vietnam, Myanmar, Thailand, Indonesia, South Korea, Pakistan, China, and Malaysia each have a higher realized output index compared to the average across all the countries. However, Myanmar, Indonesia, Pakistan, Vietnam, China, and Malaysia were the only countries with a relatively higher deviation in the output index compared to the average of all the countries. This would be reflected in the time-varying input elasticity and returns to scale estimates. Pakistan, Vietnam, Myanmar, Philippines, Indonesia, Nepal, Thailand, and Malaysia have allocated more land to agriculture production than the average of all the countries. The countries that allocated more than average also realized higher variation compared to the average, with the exception of Pakistan and Philippines.

The variation in agriculture labor and amount of labor working with agriculture production was higher in Vietnam, Bangladesh, Malaysia, Philippines, and Pakistan compared to the average of all the countries. South Korea and Nepal had the highest growth in capital and fertilizer, respectively, for the time period. Indonesia, Pakistan, India, and Vietnam allocated relatively more capital to agriculture production compared to the average and there was relatively more variation in capital allocation for the time period. Pakistan and Thailand applied more fertilizer than the average of all the countries. Thailand had the highest variation in fertilizer use for the time period. Cambodia, South Korea, and China had more livestock than the average.

IV. Empirical Application and Results[5]

Effect of accounting for technical inefficiency (Proposition 1) and time-varying estimates applying cumulative rolling regression (Proposition 2) on the elasticity of inputs, technical change, and returns to scale are examined. When using the Cobb-Douglas production function, returns to scale can be easily computed using the elasticity of input variables, technical change, and the returns to scale. Three sets of results are presented for pooled, panel, and stochastic frontier models using logs of the input and output variables. A nice feature about using logs is that the slope coefficient measures the elasticity of endogenous variables with respect to exogenous variation, that is by the percentage change in endogenous variable given a percentage change in exogenous variation. The first set of estimates does not include time trend to capture technical change, the second set of estimates include time trend to capture technical change, and finally, the country specific dummy variables are included along with time trend to capture technical change. Result of Proposition 1 is presented in Table 2 and results of Proposition 2 are presented in Tables 3 and 4, and Figures 1a and 1b.

Proposition 1: *Comparison of pool/panel models and stochastic frontier model allows the difference (over or under estimation) in input elasticity and return to scale associated with accounting for inefficiency in the estimation of production function to be quantified.*

Over or under estimation of elasticity of inputs, technical change, and returns to scale associated with accounting for inefficiency is examined by comparing the stochastic frontier production function defined in equation (3), pool model defined in equation (1), and panel model defined in equation (2). Regression results of the three models presented in Table 2 indicate all the variables are positive and significantly affect agricultural output with the exception of fertilizer. The fertilizer variable is negative and significant for the pooled and

[5] Confidence interval of parameter coefficients of pool, 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 pool, panel and stochastic frontier models.

stochastic frontier models, but positive and insignificant for the random effects model with and without time trend or technical change.

First, the results from the pooled model indicate an input elasticity of 0.86 for land which is very high relative to the other inputs. A 100 percent increase in the allocation of land to agriculture would increase the output by 86 percent, which indicates more agricultural products can be produced when more land is under agricultural production. For the pooled model accounting for time trend or technical change, the input elasticity for land is 0.88. However, once the difference across countries is accounted by country specific dummies, the input elasticity for land dropped to 0.68. Farm labor has an elasticity of 0.46 and ranks second with respect to the magnitude of contributions to agricultural output. Accounting for time trend, the input elasticity for labor reduced by more than half to 0.22 indicating the technology was labor saving. This appears to be consistent with the decline in use of labor in agriculture. With the difference across countries accounted by country specific dummies, the labor elasticity increased slightly to 0.24.

Livestock with an input elasticity of 0.30 is ranked third after land and farm labor. A 100 percent increase in the availability of livestock on the farm would increase the output by 30 percent. Accounting for technical change and difference across countries by country specific dummies, the livestock elasticity declined slightly to 0.29 and 0.27, respectively, but moved to second, followed by labor in the pooled model. Capital with an elasticity of 0.085 and fertilizer with an elasticity of -0.038 are relatively less compared to land or farm labor, showing that these inputs have a smaller positive and negative influence respectively on agricultural output. Accounting for technical change, the capital and fertilizer elasticity did not change. However, accounting for technical change and difference across countries, the elasticity of capital and fertilizer declined to 0.051 and -0.012, respectively.

To account for the availability of time series and cross-sectional data, a two-way random effects model is estimated and the results are provided in Table 2. Similar to the pooled model, the elasticity of land is 0.66 and 0.62 with and without time trend or technical change, indicating land has a strong influence on the output after accounting for the spatial variation across countries and temporal variation over time. With an elasticity of 0.52 and 0.004 for farm labor and fertilizer, respectively, the two-way random effects model indicates a relatively higher contribution to output compared to the pooled model. Accounting for time trend or technical change, the elasticity of farm labor and fertilizer reduced to 0.21 and 0.001, respectively, accounting for spatial variations across countries and temporal variations over time. However, the elasticities of 0.06 and 0.28 for capital and livestock, respectively, indicate a smaller contribution to output compared to the pooled model. The elasticity of capital and livestock was slightly different even after accounting for time trend or technical change. In general, the panel model accounting for the spatial and temporal variation increases the contribution of farm labor and fertilizer to agriculture output.

Table 2. Parameter Coefficients or Input Elasticities of Production Function for the Period, 1961-2005

	No time trend		With time trend		Country dummies	
	Coefficient	T-value	Coefficient	T-value	Coefficient	T-value
			Pooled Model			
Intercept	-3.120	-24.8	-4.009	-16.7	-4.068	-17.1
Land	0.860	33.6	0.884	34.2	0.677	24.1
Labor	0.458	15.4	0.216	3.4	0.235	3.5
Capital	0.085	19.7	0.081	18.5	0.051	9.9
Fertilizer	-0.038	-8.8	-0.038	-8.9	-0.012	-1.9
Livestock	0.300	25.0	0.289	23.9	0.267	17.5
Time trend			0.474	4.3	0.706	6.3
Returns to Scale	**1.665**		**1.432**		**1.218**	
Returns to Scale (trend)			**1.906**		**1.924**	
			Panel Model			
Intercept	-2.322	-15.7	-3.750	-14.3		
Land	0.623	20.1	0.662	25.1		
Labor	0.524	11.3	0.214	3.4		
Capital	0.059	9.8	0.052	10.9		
Fertilizer	0.004	0.5	0.001	0.2		
Livestock	0.283	9.5	0.270	18.8		
Time trend			0.668	6.1		
Returns to Scale	**1.493**		**1.199**			
Returns to Scale (trend)			**1.867**			
			Stochastic Frontier Model			
Intercept	-3.560	-31.6	-4.920	-17.5	-5.492	-5.5
Land	0.623	24.5	0.680	25.2	0.673	27.4
Labor	0.837	23.1	0.449	5.7	0.676	9.8
Capital	0.050	12.5	0.042	9.9	0.034	7.2
Fertilizer	-0.021	-4.1	-0.029	-5.5	0.0003	0.1
Livestock	0.278	26.1	0.269	23.2	0.205	16.8
Time trend			0.730	5.4	0.718	3.2
Returns to Scale	**1.767**		**1.411**		**1.589**	
Returns to Scale (trend)			**2.141**		**2.306**	

In the error component stochastic frontier model, the elasticity of land is 0.62 (compared to 0.86 and 0.62 in the pooled and panel models, respectively) but still has the largest contribution among the inputs. For the error component stochastic frontier model accounting for time trend or technical change, the input elasticity for land slightly increased to 0.68. However once the difference across countries is accounted by country specific dummies, the input elasticity for land dropped to 0.67. Land elasticity of 0.68 seems to be high compared to earlier estimates that range 0.02 to 0.42 (see Table 1 from Mundlak, Larson, and Butzer, 1997). This difference might be due to the use of longer time series, 1961-2005 and application to Asian countries. Contribution of farm labor, which has an elasticity of 0.84, seems very high compared to the pooled or panel model and earlier estimates that range from 0.03 to 0.46 (see Table 1 from Mundlak, Larson, and Butzer, 1997) without accounting for time trend or technical change. However, accounting for time trend and difference across countries, the input elasticity for labor reduced to 0.45 and 0.68, respectively. This is appropriate because even after accounting for inefficiency in the estimation of production function, more labor is used in the output production in Asian agriculture and this is reflected in the higher elasticity.

A livestock variable with an elasticity of 0.28 is not that different compared to elasticity of 0.30 and 0.28 in the pooled and panel models, respectively. For the error component stochastic frontier model accounting for technical change and difference across countries, the input elasticity for livestock decreased slightly to 0.27 and 0.21, respectively. Capital with its elasticity of less than 0.10 is still relatively low compared to land and livestock. Accounting for technical change and difference across countries, the capital elasticity decreased slightly to 0.042 and 0.034, respectively. Capital elasticity estimates are in a similar range estimated by earlier researchers.

Fertilizer with an elasticity of -0.021 compared to -0.029 and 0.0003 for the model accounting for technical change and difference across countries, respectively, is still low. Fertilizer elasticity estimated from the error component stochastic frontier model is higher compared to the panel and pooled model. Fertilizer elasticity estimates are lower than those for previous research (see Table 1 from Mundlak, Larson, and Butzer, 1997). This might be due to the relatively low use of fertilizer in Asia and substitution of labor for fertilizer.

Before comparing pool and stochastic frontier models, a comparison between a pool – panel model and panel– stochastic frontier model reveals the importance of accounting for spatial and temporal variation and inefficiency respectively. Labor and fertilizer elasticity are higher for stochastic frontier model (compared to panel) and panel (compared to pool) models. The elasticity of land, capital, and livestock are lower for stochastic frontier model (compared to panel) and panel (compared to pool) models. To quantify the differences in the input elasticity estimates accounting for inefficiency in the production function using stochastic frontier analysis, a comparison needs to be drawn between pool and stochastic frontier models without and with time trend. The elasticity of labor and fertilizer is higher in the stochastic frontier model by 0.379 and 0.017, respectively, compared to pool model. Similar higher elasticity of labor and fertilizer was estimated by stochastic frontier model accounting for time trend or technical change and difference across countries. The difference in the elasticity of labor and fertilizer was 0.233 and 0.009 (0.441 and 0.012), respectively for stochastic frontier model accounting for technical change (technical change and accounting for difference across countries with country specific dummies).

This indicates even after accounting for inefficiency in the estimation of production function, higher values seem to reflect the higher usage of labor and fertilizer in the production of output leading to higher return to scale measure. These results are quite interesting as they suggest that fertilizer is overused due to the prevalence of wetland rice in Asian agriculture and the introduction of new "green revolution" seed and technology.

In contrast, the elasticity of land, capital, and livestock are lower in stochastic frontier model by 0.237, 0.035, and 0.022, respectively compared to the pool model without accounting from time trend or technical change indicating inefficient use of these variables in the production of output. Accounting for technical change (technical change and accounting for difference across countries with country specific dummies), the elasticity of land, capital, and livestock are lower in stochastic frontier model by 0.204, 0.039, and 0.020 (0.003, 0.017, and 0.062), respectively, compared to the pool model.

Overall, the variations of agricultural output in Asia are largely explained by the input levels for land, livestock, and labor, and less so by capital and fertilizer. The estimated returns to scale from the three models are 1.67, 1.49, and 1.77, respectively, for the pooled, panel, and stochastic frontier models, meaning that a one unit change in inputs results in more than a one unit change in agricultural output. The higher return to scale estimates from a stochastic frontier model was dominated by the efficient utilization of labor. Further, it is not surprising to find strong evidence of increasing returns to scale due to small farm plots and policy. Scale economies tend to be a local measure and it is no surprise to find increasing returns to scale as the Asian farms are famously fragmented into small farm size. Programs which allow for coordination (farm coops) or plot consolation could produce some significant production gains.

Proposition 2: Time-varying parameter, β^j estimated from the equation (3) allows quantifying the extent of variation in the parameter with each additional year of information.

Tables 3 and 4 present the time-varying parameter coefficients estimated from stochastic frontier cumulative rolling regression analysis of 17 runs by addition of each year from 1986 to 2005. The mean, minimum, and maximum values of the actual and year-to-year difference in the time-varying input elasticities, technical change, and return to scale also are presented in the tables. The year-to-year difference of land, labor, capital, fertilizer, livestock, technical change, and return to scale estimated from the stochastic frontier cumulative rolling regression model[6] accounting for technical change and difference across countries is graphically presented in Figures 1a and 1b, respectively.

Time-varying parameter coefficients estimated from stochastic frontier cumulative rolling regression analysis by addition of each year from 1986 to 2005 accounting for time trend or technical change is presented in Table 3. Results from Table 3 indicate the mean elasticity of land from stochastic frontier cumulative rolling regression analysis was 0.667 with a standard deviation of 0.008. The upper and lower bound of the estimated elasticity of land is 0.682 using data from 1961-2005 and 0.654 using data from 1961-1997. The time-varying elasticity of land indicates a decreasing trend from 1961-1986 to 1961-1995. This indicates the land elasticity

[6] Similar table and graphs of input elasticity and returns to scale estimates of pooled and panel models are available from the author.

decreases at a decreasing rate with each additional year of data. Elasticity of land shows an increasing trend from 1961-1996 to 1961-2005 indicating that with each additional year of data, the land elasticity increases at an increasing rate. The mean year-to-year difference in the elasticity of land by addition of each year from 1986 to 2005 was 0.0004 with a standard deviation of 0.003.

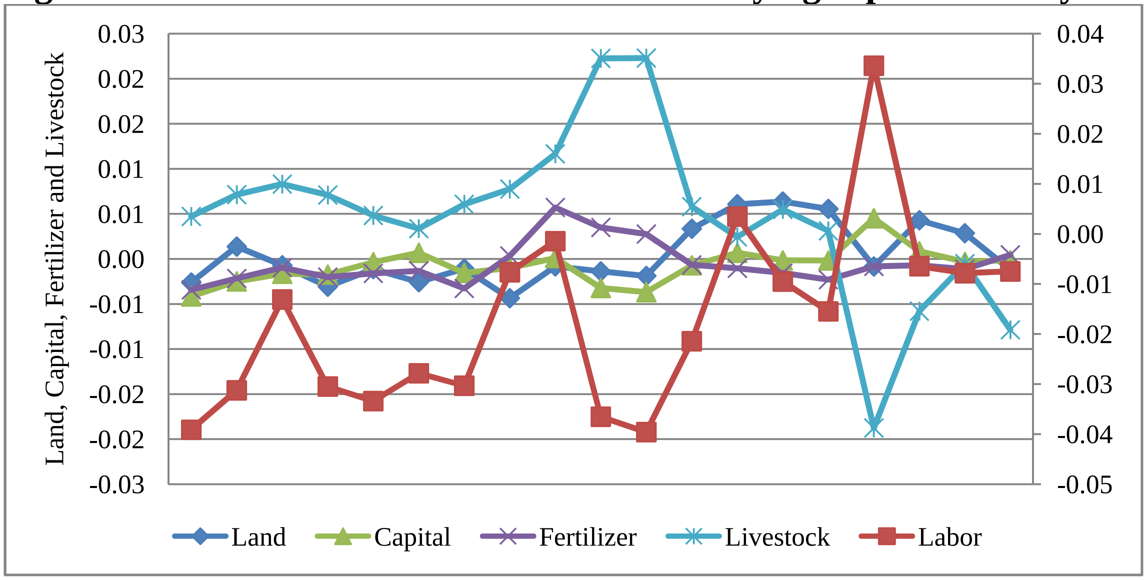
Table 3. Input Elasticities and Returns to Scale from Stochastic Frontier Cumulative Rolling Regressions, 1986-2005

Year	Land	Labor	Capital	Fertilizer	Livestock	Time trend	RTS	RTS (trend)
1961 - 1986	0.672	0.771	0.056	-0.019	0.179	0.238	1.660	1.898
1961 - 1987	0.670	0.732	0.052	-0.022	0.184	0.345	1.615	1.961
1961 - 1988	0.671	0.701	0.050	-0.024	0.191	0.409	1.588	1.997
1961 - 1989	0.670	0.688	0.048	-0.025	0.199	0.424	1.580	2.004
1961 - 1990	0.667	0.657	0.046	-0.027	0.206	0.481	1.550	2.031
1961 - 1991	0.666	0.624	0.046	-0.029	0.211	0.529	1.518	2.047
1961 - 1992	0.663	0.596	0.047	-0.030	0.215	0.570	1.490	2.060
1961 - 1993	0.662	0.566	0.045	-0.034	0.221	0.643	1.460	2.103
1961 - 1994	0.658	0.558	0.044	-0.033	0.228	0.644	1.455	2.099
1961 - 1995	0.657	0.557	0.044	-0.027	0.240	0.582	1.471	2.053
1961 - 1996	0.656	0.520	0.041	-0.024	0.262	0.596	1.455	2.051
1961 - 1997	0.654	0.480	0.037	-0.021	0.285	0.621	1.435	2.056
1961 - 1998	0.657	0.459	0.037	-0.022	0.290	0.640	1.422	2.062
1961 - 1999	0.663	0.462	0.037	-0.023	0.293	0.626	1.433	2.059
1961 - 2000	0.670	0.453	0.037	-0.024	0.298	0.635	1.434	2.069
1961 - 2001	0.675	0.437	0.037	-0.027	0.301	0.665	1.425	2.089
1961 - 2002	0.674	0.471	0.042	-0.028	0.283	0.625	1.442	2.067
1961 - 2003	0.679	0.465	0.042	-0.028	0.277	0.652	1.434	2.086
1961 - 2004	0.682	0.457	0.042	-0.029	0.276	0.683	1.428	2.111
1961 - 2005	0.680	0.449	0.042	-0.029	0.269	0.730	1.411	2.141
Mean	0.667	0.555	0.044	-0.026	0.245	0.567	1.485	2.052
Std	0.008	0.107	0.005	0.004	0.042	0.126	0.074	0.055
Minimum	0.654	0.437	0.037	-0.034	0.179	0.238	1.411	1.898
Maximum	0.682	0.771	0.056	-0.019	0.301	0.730	1.660	2.141
Mean	0.0004	-0.017	-0.001	-0.001	0.005	0.026	-0.013	0.013
Std	0.003	0.018	0.002	0.002	0.009	0.039	0.017	0.024
Minimum	-0.004	-0.040	-0.004	-0.003	-0.019	-0.061	-0.045	-0.046
Maximum	0.006	0.034	0.005	0.006	0.022	0.108	0.018	0.063

Table 4. Input Elasticities and Returns to Scale from Stochastic Frontier Cumulative Rolling Regressions with Country Dummies, 1986-2005

Year	Land	Labor	Capital	Fertilizer	Livestock	Time trend	RTS	RTS (trend)
1961 - 1986	1.597	0.617	0.037	0.0112	0.113	-1.293	2.375	1.082
1961 - 1987	1.584	0.626	0.038	0.0071	0.112	-0.890	2.368	1.478
1961 - 1988	1.260	0.654	0.036	0.0033	0.125	-0.157	2.078	1.921
1961 - 1989	1.063	0.667	0.033	0.0028	0.159	-0.173	1.926	1.753
1961 - 1990	0.869	0.664	0.018	-0.0038	0.169	0.581	1.716	2.297
1961 - 1991	0.946	0.622	0.028	0.0010	0.166	0.156	1.762	1.918
1961 - 1992	0.776	0.670	0.028	-0.0099	0.162	0.621	1.626	2.247
1961 - 1993	0.818	0.642	0.028	-0.0066	0.162	0.157	1.644	1.801
1961 - 1994	0.701	0.668	0.031	-0.0072	0.163	0.030	1.555	1.585
1961 - 1995	0.570	0.684	0.025	-0.0036	0.192	0.216	1.468	1.684
1961 - 1996	0.589	0.623	0.037	-0.0011	0.227	0.276	1.473	1.749
1961 - 1997	0.434	0.651	0.031	0.0006	0.253	0.196	1.369	1.565
1961 - 1998	0.391	0.672	0.029	0.0015	0.253	0.476	1.346	1.822
1961 - 1999	0.329	0.678	0.025	0.0028	0.262	0.700	1.297	1.997
1961 - 2000	0.319	0.660	0.021	0.0030	0.280	0.689	1.283	1.972
1961 - 2001	0.417	0.642	0.018	0.0044	0.278	1.030	1.360	2.390
1961 - 2002	0.472	0.650	0.021	0.0057	0.259	0.728	1.408	2.136
1961 - 2003	0.527	0.659	0.025	0.0035	0.245	0.647	1.460	2.107
1961 - 2004	0.582	0.670	0.028	0.0008	0.231	0.851	1.512	2.363
1961 - 2005	0.676	0.673	0.034	0.0003	0.205	0.718	1.589	2.306
Mean	0.746	0.655	0.028	0.001	0.201	0.278	1.631	1.909
Std	0.381	0.020	0.006	0.005	0.055	0.578	0.326	0.338
Minimum	0.319	0.617	0.018	-0.010	0.112	-1.293	1.283	1.082
Maximum	1.597	0.684	0.038	0.011	0.280	1.030	2.375	2.390
Mean	-0.048	0.003	0.000	-0.001	0.005	0.106	-0.041	0.064
Std	0.121	0.027	0.006	0.004	0.018	0.344	0.102	0.293
Minimum	-0.325	-0.061	-0.016	-0.011	-0.026	-0.463	-0.290	-0.446
Maximum	0.098	0.049	0.012	0.005	0.034	0.754	0.077	0.545

Figure 1a. Year to Year Difference in Time-Varying Input Elasticity



The mean elasticity of labor from stochastic frontier cumulative rolling regression analysis was 0.555 with a standard deviation of 0.107. The upper bound of elasticity of labor is 0.771 and is estimated using data from 1961-1986; the lower bound of labor elasticity is 0.437 estimated using data from 1961-2001. The time-varying elasticity of labor indicates a decreasing trend from 1961-1986 to 1961-2005 indicating the elasticity decreases at a decreasing rate with each additional year of data. The mean year-to-year difference in the elasticity of labor by addition of each year from 1986 to 2005 was -0.017 with a standard deviation of 0.018.

Elasticity of capital indicates the mean from stochastic frontier cumulative rolling regression analysis from 1986 to 2005 was 0.044 and a standard deviation of 0.005. The upper and lower bound of the estimated elasticity of capital is 0.056 using data from 1961-1986 and 0.037 using data from 1961-1997 to 1961-2001. Time-varying elasticity of capital indicates a decreasing trend from 1961-1986 to 1961-2001. The mean year-to-year difference in the elasticity of capital by addition of each year from 1986 to 2005 was -0.001 with a standard deviation of 0.002.

The mean elasticity of fertilizer from stochastic frontier cumulative rolling regression analysis was -0.026 with a standard deviation of 0.004. The upper bound of elasticity of fertilizer was -0.019 and estimated using data from 1961-1986. Similarly the lower bound of elasticity of fertilizer was -0.034 using data from 1961-1995. The time-varying fertilizer elasticities indicates a decreasing trend from 1961-1986 to 1961-1993. This indicates the fertilizer elasticity decreases at a decreasing rate with each additional year of data. Elasticity of fertilizer from 1961-1994 to 1961-2005 is a cup-shaped curve indicating the elasticity decreases, reaches a minimum, and starts to increase with each additional year of data. The mean year-to-year difference in the elasticity of fertilizer by addition of each year from 1986 to 2005 is -0.001 with a standard deviation of 0.002.

Elasticity of livestock indicates the mean of stochastic frontier cumulative rolling regression analysis from 1986 to 2005 was 0.245 with a standard deviation of 0.042. The upper and lower bound of the estimated elasticity of livestock is 0.301 using data from 1961-2001 and 0.179 using data from 1961-1986. Time-varying elasticity of livestock indicates an increasing trend from 1961-1986 to 1961-2001 and declining to the present. The mean year-to-year difference in the elasticity of livestock by addition of each year from 1986 to 2005 was 0.005 with a standard deviation of 0.009.

Elasticity of technical change indicates the mean of stochastic frontier cumulative rolling regression analysis from 1986 to 2005 was 0.567 and a standard deviation of 0.126. The lower and upper bound of the estimated elasticity of technical change is 0.238 and 0.730, respectively, in the first and the last cumulative regression. Time-varying elasticity of technical change indicates an increasing trend from 1961-1986 to the present. The mean year-to-year difference in the elasticity of technical change by addition of each year from 1986 to 2005 was 0.026 with a standard deviation of 0.039.

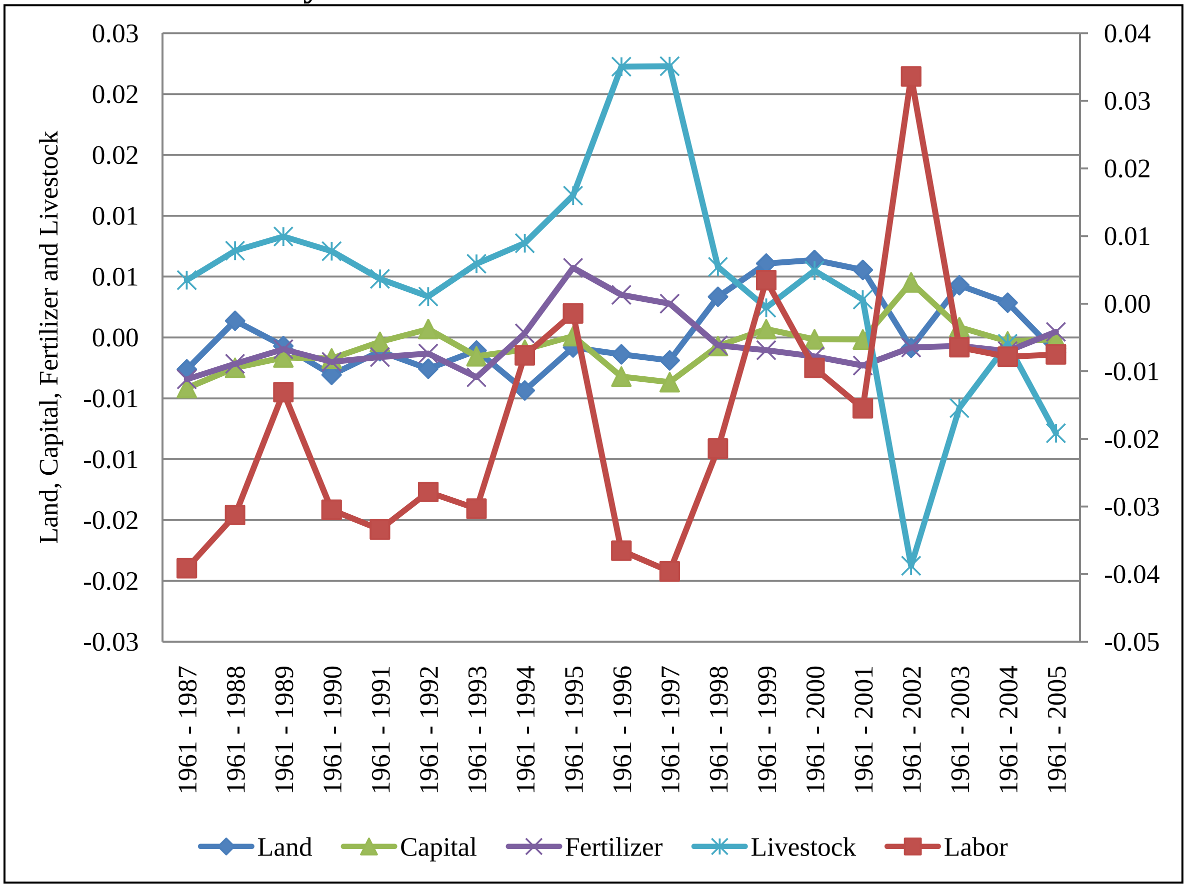
Finally, the returns to scale results indicate the mean of stochastic frontier cumulative rolling regression analysis from 1986 to 2005 was 1.485 and a standard deviation of 0.074. The upper and lower bound of the return to scale is 1.66 using data from 1961-1986 and 1.411 using data from 1961-2005, indicating a declining trend in the return to scale. However with the addition of technical change, the returns to scale results indicate a higher mean of 2.052 for the stochastic frontier cumulative rolling regression analysis from 1986 to 2005 and an increasing return to scale.

Time-varying input elasticity, technical change and return to scale estimated from the error component stochastic frontier model accounting for technical change and difference across countries is presented in Table 4. Compared to results in Table 3, the mean and standard deviation of time-varying land elasticity was higher with a value of 0.746 and 0.381 respectively. However the trend in the time-varying elasticity of land was quite similar to the model accounting for technical change. The mean year-to-year difference in the elasticity of land for addition of each year from 1986 to 2005 was -0.048 with a standard deviation of 0.121.

Mean elasticity of labor from stochastic frontier cumulative rolling regression analysis was around 0.655 with a standard deviation of 0.02 for the error component stochastic frontier model accounting for technical change and difference across countries. Unlike a clear trend in the time-varying labor elasticity estimated from model accounting for technical change, in this case there is variation in the labor elasticity. The mean year-to-year difference in the elasticity of labor from stochastic frontier cumulative rolling regression analysis by addition of each year from 1986 to 2005 was 0.003 with a standard deviation of 0.0127. Similar to labor, there is no clear trend in the time-varying elasticity of capital. The mean of stochastic frontier cumulative rolling regression analysis from 1986 to 2005 was 0.028 with a standard deviation of 0.006. The mean year-to-year difference was almost zero with a standard deviation of 0.006.

The mean elasticity of fertilizer from stochastic frontier cumulative rolling regression analysis was 0.001 with a standard deviation of 0.005. The time-varying elasticity of fertilizer indicates decreasing positive trend from 1961-1986 to 1961-1989, decreasing negative trend from 1961-1990 to 1961-1996, increasing trend from 1961-1999 to 1961-2002 and a decline thereafter. The mean year-to-year difference in the elasticity of fertilizer was -0.001 with a standard deviation of 0.004. Time-varying elasticity of livestock indicates an increasing trend from 1961-1986 to 1961-2000 and declining to the present. The mean year-to-year difference in the elasticity of livestock was 0.005 with a standard deviation of 0.018.

Figure 1b. Year to Year Difference in Time-Varying Input Elasticity With Country Dummies



Elasticity of technical change indicates the mean of stochastic frontier cumulative rolling regression analysis from 1986 to 2005 was 0.278 and a standard deviation of 0.578. Unlike a clear trend in the time-varying technical change estimated from model accounting for technical change, variation in the technical change is experienced accounting for difference across countries. The mean year-to-year difference in the elasticity of technical change from stochastic frontier cumulative rolling regression analysis was 0.106 with a standard deviation of 0.344.

Returns to scale results indicate the mean of stochastic frontier cumulative rolling regression analysis from 1986 to 2005 was 1.631 and a standard deviation of 0.326. However with the addition of technical change, the returns to scale results indicate the mean of stochastic frontier cumulative rolling regression analysis from 1986 to 2005 was 1.909 and a standard deviation of 0.338. Trends in the time-varying return to scale indicate an increasing trend with technical change in the model and a decreasing trend without the technical change in the model.

V. Conclusions

In this paper, first the importance of accounting for technical efficiency on the input elasticities, technical change, and calculation of returns to scale as defined in proposition 1 is examined. Accounting for inefficiency in the estimation of production has important implications including the ability to quantify the gap between crops grown under ideal conditions (technical experimental station data) and performance in the field, and across countries due to transfer of "new" technology (seed, equipment, etc). At the disaggregate level this information would be useful for farmers, regional officials, rural banks, and input suppliers as to the input variables driving output and ultimately their profitability. At the aggregate level it is useful for policy makers as it will provide information on future investments of technology innovations of inputs to improve output and profitability for overall growth of the economy.

Second, the importance of each additional year of data or information on the input elasticities, technical change estimates, and calculation of returns to scale as defined in proposition 2 is quantified applying cumulative rolling regression. In the context of production function, input elasticities, technical change, and returns to scale were assumed to be systematic (constant over time) and driven by state, national, and worldwide differences. However, the time-varying input elasticities, technical change, and returns to scale is estimated to examine the changes in the industry induced by the yearly advancements in structure of agriculture production.

Both analyses are conducted using the stochastic frontier analysis of primal Cobb-Douglas production functions with an application to Asian agriculture data from 1961-2005. 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 estimation. Second, earlier studies assumed input elasticities, technical change, and returns to scale to be systematic over time and driven by state, national, and worldwide difference. The time-varying estimates of input elasticities, technical change, and returns to scale estimated using cumulative rolling regression provide evidence of variation in the measures with each additional year of data or information.

Estimates from this study indicate returns to scale are underestimated by the traditional pooled and panel compared to stochastic frontier model that accounts for inefficiency. These results are slightly different from earlier research results for two good reasons. First, 1961-2005 time period follows the onset of green revolution especially in the Asian countries. Also, the returns to scale are overestimated by earlier research as they used time-series, pooled, and panel models that do not account for technical inefficiency as stochastic frontier analysis.

Time-varying estimates of input elasticities, technical change, and returns to scale indicate variations with each additional year of information. Further the time-varying input elasticities, technical change, and returns to scale indicate variations across inputs and over time questioning the systematic nature due to changes in the industry induced by the advancements in structure of agriculture production, investments, and domestic and international policies over time.

References

Aigner, D.J., C.A.K. Lovell, and P. Schmidt. (1977). “Formulation and Estimation of Stochastic Frontier Production Function Models”. *Journal of Econometrics*, 6, 21-37.

Arnade, C. (1998). “Using a Programming Approach to Measure International Agricultural Efficiency and Productivity”. *Journal of Agricultural Economics*, 49, 67-84.

Battese, G.E. and T.J. Coelli. (1992). “Frontier Production Functions, Technical Efficiency and Panel Data: With Application to Paddy Farmers in India”. *Journal of Productivity Analysis*, 3, 153-169.

Battese, G.E. and T.J. Coelli. (1995). “A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data”. *Empirical Economics*, 20, 325-332.

Basu, S. and J. Fernald. (1997). Returns to Scale in U.S. Production: Estimates and Implications”. *Journal of Political Economy*, 105, 249–83.

Bauer, P.W. (1990). “Recent Developments in the Econometric Estimation of Frontiers”. *Journal of Econometrics*, 46, 39-56.

Bureau, C., R. Färe, and S. Grosskopf. (1995). “A Comparison of Three Nonparametric Measures of Productivity Growth in European and United States Agriculture”. *Journal of Agricultural Economics*, 46, 309-326.

Chiang, T.C. (May 1988). “The Forward Rate as a Predictor of the Futuer Spot Rate- A Stochastic Coefficient Approach”. *Journal of Money, Credit, and Banking*, 20 (No. 2): 212-232.

Crockett, J.H., F.E. Nothaft, and G.H.K. Wang. (1991). “Temporal Relationships Among Adjustable-Rate Mortgage Indexes”. *Journal of Real Finance and Economics*, 4: 409-419.

Fare, R., S. Grosskopf and C.A.K. Lovell. *Production Frontiers*. Cambridge: Cambridge University Press, 1994.

Farrell, M.J. (1957). ‘The Measurement of Productive Efficiency’. *Journal of the Royal Statistical Society Series A*, 120, pp. 253-90.

Fisher, L. and J.H. Kamin. (June 1985). “Forecasting Systematic Risk: Estimates of "Raw" Beta that Take Account of the Tendency of Beta to Change and the Heteroskedasticity of Residual Returns”. *The Journal of Financial and Quantitative Analysis*, 20(No. 2):127-149.

Forsund, F.R., C.A.K. Lovell, and P. Schmidt. (1980). “A Survey of Frontier Production Functions and of their Relationship to Efficiency Measurement”. *Journal of Econometrics*, 13, 5-25.

Greene, W.H. (1993). “The Econometric Approach to Efficiency Analysis”. in Fried, H.O., Lovell, C.A.K. and Schmidt, S.S.(Eds), *The Measurement of Productive Efficiency*, Oxford University Press, New York, 68-119.

Groeneworld, N. and P. Fraser. (1999). “Time-varying Estimates of CAPM Betas”. *Mathematics and Computers in Simulation*, 48 (4-6 or June): 531-539.

Hayami Y. (1969). “Sources of Agricultural Productivity Gap Among Selected Countries”. *American Journal of Agricultural Economics* 51, pp. 564-75.

Hayami Y. (1970). “On the Use of the Cobb-Douglas Production Function on the Cross-Country Analysis of Agricultural Production”. *American Journal of Agricultural Economics* 52, pp. 327-329.

Hayami, Y. and V. Ruttan. (1970). “Agricultural Productivity Differences Among Countries”. *American Economic Review*, 40, 895-911.

Hayami, Y. and V. Ruttan. (1971). *Agricultural Development: An International Perspective.* Johns Hopkins Press, Baltimore.

Heady, E.O. (1944). “Production Functions from a Random Sample of Farms”. *Journal of Farm Economics,* 28 (4), pp. 989-1004.

Heady, E.O. and J.L. Dillon. (1961). *Agricultural Production Functions*. Ames: Iowa State University Press.

Kawagoe, T. and Y. Hayami. (1983). “The Production Structure of World Agriculture: An Intercountry Cross-Section Analysis”. *Developing Economies*, 21, 189-206.

Kawagoe, T. and Y. Hayami. (1985). “An Intercountry Comparison of Agricultural Production Efficiency”. *American Journal of Agricultural Economics*, 67, 87-92.

Kawagoe, T., Y. Hayami and V. Ruttan. (1985). “The Intercountry Agricultural Production Function and Productivity Differences Among Countries”. *Journal of Development Economics*, 19, 113-132.

Kumbhakar, S. and K. Lovell. *Stochastic Frontier Analysis*. Cambridge University Press, Cambridge, 2000.

Lawrence, F. and J.H. Kamin. (1985). “Forecasting Systematic Risk: Estimates of Raw Beta that take Account of the Tendency of Beta to Change and the Heteroskedasticity of Residual Returns”. *The Journal of Financial and Quantitative Analysis*, 20(2 or June): 127-149.

Meeusen, W. and J. van den Broeck. (1977). “Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error”. *International Economic Review*, 18, 435-444.

Mundlak, Yair, Donald F. Larson, and Rita Butzer. "The Determinants of Agricultural Production: A Cross-Country Analysis". Policy Research Working Paper 1827 (Washington, D.C.: The World Bank, 1997).

Nin, A., C. Arndt, and P.V. Preckel. (2003). "Is agricultural productivity in developing countries really shrinking? New evidence using a modified nonparametric approach". *Journal of Development Economics*, 71, 395-415.

Rao, D.S.P. and T.J. Coelli. (2003). Catch-up and Convergence in Global Agricultural Productivity. Brisbane. *Center for Efficiency and Productivity Analysis, University of Queensland*, 24p.

Rosenberg, B. and J. Guy. (1976). "Prediction of Beta from Investment Fundamentals". *Financial Analysts Journal*, 32(3): 60-72.

Schmidt, P. (1986). "Frontier Production Functions". *Econometric Reviews*, 4, 289-328.

Smith, R.J., and A.A.R. Taylor. (2001). "Recursive and Rolling Regression-based Tests of the Seasonal Unit Root Hypothesis". *Journal of Econometrics*, 105: 309-336.

Solow, R.M. (1957). "Technical Change and the Aggregate Production Function". Review of Econometrics and Statistics 39 (3), pp.312-20.

Trueblood, M.A. (1991). Agricultural Production Functions Estimated from Aggregate Intercountry Observations: A Selected Survey. U.S. Department of Agriculture, Economics Research Service, Staff Report No. AGES9132.