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A Comparison of Intercountry Agricultural Production Functions: A Frontier Function Approach

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Unlike the work by Hayami and Ruttan in the 1970s, this study utilizes frontier meta-production functions to study intercountry agricultural productivity differences. Technical efficiency differences are examined through estimation of deterministic and stochastic frontiers for 43 countries over 1960, 1970 and 1980. In most cases, developed countries on average have higher technical efficiency levels. However, not all developed countries are fully technically efficient while certain developing countries perform comparably with other developed countries. The results also show that the productivity gap between developing and developed countries has increased over time. Yet there is potential to improve productivity of developing countries, especially by expanding their human capital stock, as indicated by high output elasticities for primary and secondary education and technical education.

I. Introduction

Research techniques available to explore the area of agricultural productivity include economic modeling and the case study approach. Production functions have been extensively used in explaining differences in agricultural productivity among countries. Since the introduction of the metaproduction function by Hayami and Ruttan in 1970, many studies have utilized this concept in related work (Kawagoe and Hayami (1985), Binswanger *et al*. (1987), Lau and Yotopoulos (1989), Frisvold and Lomax (1991), Boskin and Lawrence (1992)).[1] This approach is based on the simple assumption that all countries have access to the same technology, but that each may operate on a different portion of the function due to specific country situations. An extensive survey of current available literature shows that past studies have estimated average metaproduction functions to explain intercountry agricultural productivity differentials. However, estimation of average functions are not consistent with the notion of maximum output.

The general objective of this paper is to apply the frontier approach to estimate metaproduction functions explaining intercountry agricultural productivity differentials and

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1. The metaproduction function is defined as an envelope of the most efficient points of production for any given industry among countries in the world (Hayami and Ruttan (1970)).

compare these productivity results with the research previously done by Hayami and Ruttan. The next section will review the literature on metaproduction functions and the frontier function approach. Subsequently, empirical estimation of metaproduction functions via the frontier approach will follow and these results will be compared with Hayami and Ruttan's earlier metaproduction results. Conclusions and implications will be drawn in the last section of the paper.

II. Approaches

For a firm producing a single output using multiple inputs, overall economic efficiency was decomposed into two components by Farrell (1957), viz., technical and allocative (price) efficiencies. Fare, Grosskopf and Lovell (1985) identified another component, structural efficiency, and found that comparisons in efficiency could also be made using monetary values associated with a firm, such as costs, revenues, and profits. Research presented in this paper concentrates on technical efficiency or the process of transforming inputs into outputs such that the firm operates on the boundary of the production set.

In their pioneering work, Hayami (1969) and Hayami and Ruttan (1970, 1985), used the concept of the metaproduction function to explain differences in agricultural productivity, at the global level. While metaproduction functions are attributed to Hayami and Ruttan, the authors themselves acknowledge the concept as being implicit in the work of Brown (1966) and Salter (1960). An important assumption made by Hayami and Ruttan (1970) was that a single a production function could be utilized to depict technical possibilities available for a specific industry, in different countries or regions. However, it is noted that producers do not operate on a universal microproduction function. What Hayami and Ruttan (1970) specified as the secular or metaproduction function is the envelope of all countries' production possibilities, given their resource endowments and technologies.

Following the work by Hayami and Ruttan (1970, 1985), several studies have attempted to estimate intercountry aggregate metaproduction functions. Lau and Yotopolous (1989) have re-estimated the Kawagoe-Hayami-Ruttan model by using the transcendental logarithmic form of the production function in lieu of the Cobb-Douglas production function and data in differenced form to allow for country-specific productivity differences to be captured as part of the unexplained residual. Although this provided more reasonable results, the estimated metaproduction function still falls short of being an envelope type function.[2] Boskin and Lawrence (1992) estimated an aggregate metaproduction function for the Group-of-Five (G-5) countries (France, West Germany, Japan, United Kingdom and United States) using a transcendental logarithmic production function. They utilize the estimated intercountry, aggregate metaproduction function to compare productive efficiencies between these G-5 countries.

Since Farrell's work in 1957, numerous studies have considered frontier functions. The attraction of frontier functions is attributed to their conceptual consistency with economic

2. Lau and Yotopoulos (1989) discuss the new opportunities as well as the problems (e.g., non-comparability of data, differences in economic environment and functional form specification) associated with pooled intercountry data.

optimization theory (Bauer (1990)). Deviations from the estimated frontier function can serve as a measure of relative efficiency (Mbelle and Sterner (1991)).

Frontier models can be estimated as either primal or dual functions. The advantages of both types of models have been discussed elsewhere (Timmer (1971), Forsund *et al*. (1980), Kumbhakar (1990), and Battese (1992)). Frontier functions can also be constructed using either mathematical or econometric approaches. These two approaches utilize different techniques to envelop the data. The econometric approach, though stochastic and able to separate effects from noise and inefficiency, faces possible specification error in assuming a specific functional form of the frontier. The programming approach, on the other hand, has the advantage that models can be formulated with (e.g., linear and quadratic programming) or without (DEA) restrictions on functional form. A flaw with the standard DEA model is that it does not easily incorporate random noise. However, recent work in applying bootstrapping techniques helps remedy this shortcoming (Simar and Wilson (1998) and Lothgren and Tambour (1999)).

Different technical efficiency measures that were obtained using average and frontier functions have shown varying results, especially in the measurement of the intercept term. Bravo-Ureta and Rieger (1990) suggest that frontier functions are corrected (for the intercept) average functions. Depending on the research objective(s), choice between average and frontier functions could be critical. For instance, if the objective is to measure technical efficiency, then the use of average production functions would project only average responses and not necessarily the most efficient responses.

III. Efficiency Measurement

There are three basic tasks that need to be fulfilled in measuring technical efficiency (Fare *et al*. (1985)). The first step is to specify the behavioral objective for the unit of study. This may be output, revenue or profit maximization or cost minimization for the production unit. Once the objective is determined, the technology must be specified. At this stage, there are two techniques that could be adopted, viz., nonparametric or parametric. With the above decision made, the last requirement is to apply actual computational methods, which will quantify technical efficiency of the unit under study. The technique chosen will depend on the decision made regarding the technology specification.

The econometric estimation of nonparametric models is still an emerging field. Earlier studies in nonparametric modeling concentrated on mathematical estimation techniques. Recently, data envelopment analysis (DEA) has gained popularity as a means of estimating nonparametric models. The work by Sengupta (1989) provides a useful review involving econometric estimation of nonparametric frontier models.

Parametric estimation differs from nonparametric estimation in that parameters are statistically estimated. In addition, the models are capable of allowing for non-constant returns to scale, which was a limitation of Farrell's model. Extensions by Farrell and Fieldhouse (1962) and Seitz (1971) to non-constant returns to scale technologies helped remove these model restrictions. Parametric estimation of frontier functions can utilize both econometric methods and mathematical programming techniques.

IV. Deterministic versus Stochastic Frontiers

The main feature of stochastic frontier functions is the "composed" error term. The composed nature of the error term allows presence of factors that might affect the efficiency of the unit in question. Whereas deterministic functions consider any deviation from the frontier to be caused by inefficiencies and/or statistical noise, both due to measurement errors and incomplete specification of functions, stochastic frontiers account for these deviations via the composed error term.

Stochastic frontier functions were first proposed independently by Aigner, Lovell and Schmidt (1977) and Meeusen and Van den Broeck (1977). The general model is specified as:

$$Y_i = f(x_i, B)\exp(V_i - U_i)\ , \qquad (1)$$

where Y_i = output,

X_i = input,

B = vector of other factors affecting output, and

V_i, U_i = error components.

The error component V_i is a random error with zero mean, that reflects random deviations due to factors outside the control of the production unit. Influence of weather factors and economic conditions set exogenously as well as measurement errors could be included in this error component. The second component of the disturbance term, U_i, is restricted to be non-negative, and is attributed to firm effects, resulting from inefficiencies due to factors within the control of each firm. While the random errors, V_i, were assumed to be independently and identically distributed as $N(0, s_v^2)$ random variables, the technical efficiency, effects, U_i, follow distributions such as half normal, truncated normal, exponential, and gamma distributions. Decomposition of the disturbance term allows for better identification of actual technical efficiency/inefficiency.

Parametric deterministic production functions are estimated by defining a half-truncated error term and applying the Minimum Absolute Deviation (MAD) technique to minimize total absolute deviations via linear programming or LP (Aigner and Chu (1968) and Timmer (1971)).[3] The basic LP setup is presented as:

$$\text{Minimize} \sum_{t=1}^{T} \sum_{i=1}^{n} |e_{it}| = \sum_{t=1}^{T} \sum_{i=1}^{n} \left| Y_{it} - (A_0 + \sum_{k=1}^{m} a_k x_{itk}) \right| \qquad (2)$$

subject to :

3. Variants of this technique include studies by Forsund and Jansen (1977) and Forsund and Hjalmarsson (1979). Translog frontiers with subsidiary constraints have been developed by Nishimizu and Page (1982) for a production frontier and by Charnes, Cooper and Sueyoshi (1988) for a cost frontier.

$$A_0 + \sum_{k=1}^{m} a_k x_{itk} \geq Y_{it} \text{ for all } i \text{ and } t.$$

Given the stochastic nature of agricultural production and being consistent with Hayami and Ruttan (1970 and 1985), the production function approach was selected in the current study. Data availability in terms of input quantities was another reason to select the production function approach to study production efficiency instead of using a dual approach.

In this study, the deterministic production frontier was estimated by linear programming using the software package LINDO (LINDO Systems, Inc. (1993)). The software package FRONTIER Version 2.0 (Coelli (1992)) was used to estimate the stochastic frontier production functions. This package allows a three-step procedure to obtain maximum likelihood estimates. The stochastic frontier specified in Equation (1) is expanded below to describe the frontier functions estimated by FRONTIER 2.0:

$$Y_{it} = f(x_{it}; B)\exp(V_{it} - U_{it}) \qquad i = 1,2,\ldots\ldots\ldots, N, \qquad t = 1,2,\ldots\ldots\ldots, T, \tag{3}$$

where V_{it} = error term of random disturbances, distributed i.i.d. $N(0, s_v^2)$.

$U_{it} = U_i \exp(-h(t-T))$ is the country specific error term due to inefficiency, with h an unknown scalar parameter, U_i having half-normal distribution (i.i.d. non-negative truncations of $N(m, s_v^2)$ with m and s_v^2 being mean and variance of the distribution respectively).

The stochastic frontier production function was estimated with no restrictions imposed on the mean of the country-specific error distribution (m). This error specification is considered to be a generalized version of $m = 0$ specification, which is more widely seen in the literature (Alauddin, Squires and Tisdell (1993))

V. Data

This study draws heavily from data used by Hayami and Ruttan (1985) with modifications to certain variables, to account for consistency. Hayami and Ruttan's study analyzed data from 1960, 1970 and 1980. Country classification of developing and developed nations adopted by Hayami and Ruttan was maintained.[4] This data set was then used to estimate average and frontier metaproduction functions. Average functions were estimated to ascertain consistency of current estimation with those obtained by Hayami and Ruttan (1985).

The dependent variable used was aggregate agricultural output. Explanatory variables

4. Hayami and Ruttan categorized countries into developing and developed, based on 1980 per capita income levels. Countries with a per capita income of above U.S. $4,000 are classified as developed countries and those whose per capita income was below U.S. $4,000 are in the category of developing countries.

included male workers in agriculture, agricultural land area, (weighted) livestock index, total fertilizer consumption, total tractor horsepower, primary education (with a proxy of either the literacy ratio or the enrollment rate in primary and secondary schools), and a measure of technical education (with a proxy of the number of agricultural graduates per 10,000 male farm workers). Hayami and Ruttan rationalize that these seven primary explanatory variables represented the effects of resource endowments (land and livestock), technology (machinery and fertilizer) and human capital (general and technical education), on agricultural productivity.

VI. Estimation Results

Average (OLS) metaproduction functions were first estimated with the data from Hayami and Ruttan (1985). Although not an exact match, the estimated OLS results were comparable to Hayami and Ruttan. However, this study's estimates exactly matched the results of Lau and Yotopoulos (1989) who used the same Hayami-Ruttan data set for pooling all countries across the three time periods. Estimates for the two models are reported in Tables 1 and 2 whereby these models are differentiated based on the measure of primary education used (i.e., literacy ratio versus enrollment in primary and secondary schools). Model 1 refers to those models where primary education is represented by the country's literacy ratio. The second model uses primary and secondary school enrollment rates to replace the literacy rate as the measure of primary education. The deterministic frontier was estimated by linear programming while the stochastic frontier was estimated via a maximum likelihood procedure.

Table 1 OLS Metaproduction Function Estimates (43 countries)
Pooling Data from 1960, 1970 and 1980

Regression	H-R[1] 1985 (Model 1)[2]	H-R 1985 (Model 2)	Re-estimated K-H-R by L-Y[3] (Model 1)	Re-estimated K-H-R by L-Y (Model 2)
Labour	0.509*	0.503*	0.560*	0.555*
	(7.49)[4]	(7.40)	(7.99)	(7.91)
Land	0.036	0.033	0.035	0.032
	(1.03)	(0.94)	(1.01)	(0.92)
Livestock	0.302*	0.309*	0.293*	0.299*
	(6.43)	(6.44)	(6.30)	(6.37)
Fertilizer	0.158*	0.154*	0.154*	0.150*
	(4.05)	(3.85)	(4.01)	(3.85)
Machinery	0.61	0.67*	0.70*	0.076*
	(1.69)	(1.91)	(2.00)	(2.19)
General Education				
a. Literacy Ratio	0.139		0.123	
	(1.53)		(1.38)	
b. School Enrollment		0.165		0.149
		(1.29)		(1.19)

Table 1 (Continued)

Regression	H-R[1] 1985 (Model 1)[2]	H-R 1985 (Model 2)	Re-estimated K-H-R by L-Y[3] (Model 1)	Re-estimated K-H-R by L-Y (Model 2)
Technical Education	0.180*	0.174*	0.181*	0.176*
	(5.81)	(5.44)	(6.03)	(5.63)
LDC Dummy	−0.444*	−0.446*	−0.461*	−0.465*
	(−4.00)	(−4.02)	(−4.23)	(−4.25)
Time Dummy: 1970	−0.004	−0.021	−0.001	−0.016
	(−0.06)	(−0.30)	(−0.02)	(−0.23)
1980	−0.044	−0.070	−0.041	−0.064
	(−0.54)	(−0.86)	(−0.51)	(−0.80)
Constant			1.906*	1.815*
			(4.79)	(3.40)
Adjusted R^2	0.943	0.943	0.950	0.950
Returns to Scale	1.066*	1.066*	1.112*	1.112*
	(22.68)	(22.21)	(2.25)	(2.24)

[1] H-R denotes Hayami and Ruttan: K-H-R denotes Kawagoe, Hayami and Ruttan: and L-Y denotes Lau and Yotopolous.

[2] Model 1 uses the literacy ratio to represent general education while Model 2 uses school enrollment to proxy general education.

[3] This study's estimated results are exactly the same as those obtained by Lau and Yotopolous.

[4] Figures in parentheses represent t-statistics. An asterisk (*) denotes statistical significance at the 5% level.

Table 2 Frontier Metaproduction Function Estimates (43 countries) Pooling Data from 1960, 1970 and 1980

Estimation Method Model	Deterministic Frontier LP[1]		Stochastic Frontier MLE	
	(Model 1)[2]	(Model 2)	(Model 1)	(Model 2)
Labour	0.792	0.823	0.356	0.328*
			(1.13)[3]	(4.08)
Land	0.029	0.011	0.083	0.150*
			(1.44)	(2.91)
Livestock	0.259	0.274	0.352*	0.313*
			(2.27)	(5.62)
Fertilizer	0.053	0.045	0.131	0.102*
			(1.93)	(2.73)
Machinery	0.086	0.094	0.068	0.070*
			(1.30)	(2.57)
General Education				
a. Literacy Ratio	0.327		−0.188	
			(−0.86)	
b. School Enrollment		0.495		−0.363
				(−3.27)

Table 2 (Continued)

Estimation Method Model	Deterministic Frontier LP[1]		Stochastic Frontier MLE	
	(Model 1)[2]	(Model 2)	(Model 1)	(Model 2)
Technical Education	0.170	0.170	0.176 (0.72)	0.131* (4.48)
LDC Dummy	−0.557	−0.535	−0.343	−0.911*
Time Dummy: 1970	0.017	−0.015		
1980	0.165	0.100		
Constant	1.394	0.700	3.503* (5.10)	4.946* (5.91)
Mu			0.535	0.928*
Eta			−0.015	0.097*
Returns to Scale	1.219	1.247	0.990 (−0.03)	0.963 (−0.57)

[1] LP and MLE denote linear programming and maximum likelihood estimation respectively.

[2] Model 1 uses the literacy ratio to represent general education while Model 2 uses school enrollment to proxy general education.

[3] Figures in parentheses represent asymptotic t-statistics. An asterisk (*) denotes statistical significant at the 5% level.

For both average and frontier metaproduction functions, labour had the largest impact on agricultural production. Estimated coefficients have positive signs as expected, except for coefficients for primary education in the stochastic frontier case (although statistically different from zero for only one of the two estimated models). A possible explanation for the negative coefficients is that developed countries' higher primary education measures are able to mask the positive effect that would be found for developing countries.

Of interest is the estimated coefficients on the LDC dummy variable. The significant results for the OLS regression and Model 2 Stochastic Frontier (SF) suggest that developing countries had a negative impact on overall agricultural productivity. While coefficients obtained from the Deterministic Frontier (DF) models could not be subjected to statistical testing, they were consistent in direction but larger in absolute value than OLS and SF results.

The effect of time from the pooling of cross section and time series was mixed and statistically insignificant in the OLS case. Returns to scale for the conventional inputs, viz., labour, land, livestock, fertilizer and machinery, were estimated as the summation of the relevant output elasticities. Statistical testing indicated the presence of increasing returns to scale for the average metaproduction functions.[5] Returns to scale for the stochastic metaproduction frontier were 0.990 and 0.963 for Models 1 and 2 respectively. Unlike the case of average metaproduction functions, these values were not statistically different from one (using t-test), indicating constant returns to scale.

5. The returns to scale coefficients for Hayami and Ruttan and our studies are 1.066 and 1.112, respectively. Results of an F-test showed that these scale effects were not statistically different.

One would expect the frontier metaproduction functions to lie above the OLS metaproduction function. Frontier output levels and average output levels were calculated first for the complete set of 43 countries.[6] All estimated frontier output levels are above their corresponding OLS estimates, even when their intercept terms are lower. The estimated output levels associated with stochastic frontiers are distributed both above and below those associated with deterministic frontiers.

A wide variation in technical efficiencies was found in the frontier metaproduction functions estimated (see Table 3). This is to be expected, since the countries considered in the study represent different stages of development. Whereas certain countries reached technical efficiencies of 90% or more, no country achieved full technical efficiency (100%), in either the deterministic or stochastic formulations. Average technical efficiencies estimated for the deterministic and stochastic models were 66.80% and 59.23% (for Model 1) and 68.30% and 37.67% (for Model 2). Paired t-tests indicated that the average technical efficiencies generated by the deterministic frontiers were statistically higher than those from the estimated stochastic frontiers at the 5% significance level.

Table 3 Distribution of Technical Efficiencies for All Countries (Percentage of Sample)

	Model 1		Model 2	
Technical Efficiency	LP	ST	LP	ST
100%	0.00	0.00	0.00	0.00
90.0-99.9%	6.98	6.98	4.65	0.00
80.0-89.99%	18.60	6.98	27.91	4.65
70.0-79.99%	16.28	4.65	18.60	0.00
60.0-69.99%	25.58	30.23	18.60	2.33
50.0-59.99%	13.95	23.26	13.95	4.65
40.0-49.99%	11.63	16.28	11.63	23.26
30.0-39.99%	4.65	6.98	4.65	37.21
20.0-29.99%	2.33	4.65	0.00	23.26
10.0-19.99%	0.00	0.00	0.00	4.65
Total[1]	100.00	100.00	100.00	100.00
Average Efficiency (%)	66.80	59.23	68.30	37.67

[1] Differences due to rounding.

Ranking of the 43 countries, according to each frontier, is presented in Tables 4 and 5. Developed countries have a larger number (share) of countries which have technical efficiencies exceeding the computed average or mean efficiency level. In general, technical efficiencies of developed countries tend to be higher than that for developing countries (with the exception of the stochastic estimates in Model 2).

6. Due to space limitations, estimated frontier and OLS output levels are not shown here but can be found in Kudaligama (1994).

Table 4 Country Ranking of Technical Efficiencies
All Countries (Model 1)

	LP		ST
Paraguay	29.69	Libya	25.55
Mexico	38.27	Paraguay	28.77
S. Africa	38.39	Pakistan	35.24
Philippines	42.15	India	35.62
Japan	43.84*	Ireland	39.80*
Ireland	43.92*	Mexico	42.75
India	45.82	Norway	43.17*
Libya	48.66	Peru	45.34
Yugoslavia	50.91	Yugoslavia	45.53
Venezuela	51.44	S. Africa	46.29
Greece	51.58*	Venezuela	46.62
Chile	54.40	Egypt	48.94
Brazil	59.00	Chile	50.00
Egypt	59.98	Finland	51.29*
U.K.	61.63*	Brazil	52.82
Peru	63.35	Japan	53.70*
Norway	63.57*	Australia	54.12*
Colombia	64.55	Turkey	55.94
Spain	65.10*	Bangladesh	56.01
Pakistan	65.20	Greece	56.07*
Finland	66.41*	Philippines	56.71
Netherlands	66.53*	U.K.	58.12*
Switzerland	66.71	Colombia	60.05
Turkey	67.44	Austria	60.36**
Bangladesh	69.79	Syria	60.86
Sri Lanka	73.77	USA	60.94**
Italy	75.02**	New Zealand	61.27**
Germany, F.R.	75.31**	Sweden	63.34**
Austria	75.54**	Germany, F.R.	63.37**
Denmark	75.58**	Canada	64.59**
Sweden	77.58**	Portugal	67.43
Syria	78.29	Denmark	67.60**
Taiwan	82.90	Switzerland	68.96**
Canada	82.96**	Spain	69.15**
Mauritius	84.29**	Netherlands	69.83**
Portugal	84.60	Belgium	72.17**
Australia	84.60**	Italy	78.96**
France	86.18**	Sri Lanka	80.83
New Zealand	86.64**	France	80.86**
Israel	88.99**	Israel	89.02**
USA	91.24**	Argentina	91.50
Belgium	91.28**	Taiwan	92.59
Argentina	98.61	Mauritius	94.71
Average	66.80	Average	59.23

[1] An (*) to the right of the computed technical efficiency denotes developed countries below the computed average level of technical efficiency and (**) denotes developed countries above the average.

Table 5 Country Ranking of Technical Efficiencies
All Countries (Model 2)

	LP		ST
Paraguay	31.90	Libya	15.18
S. Africa	35.78	Paraguay	18.35
Philippines	40.14	Ireland	20.05*
Mexico	41.22	Pakistan	22.92
Japan	43.37*	Australia	23.47*
Ireland	45.11*	Norway	23.60*
India	45.58	Greece	25.65*
Yugoslavia	51.16	India	25.88
Greece	52.51*	Finland	26.49*
Venezuela	53.02	Spain	28.90*
Libya	54.37	Mexico	29.12
Chile	54.67	Austria	29.52*
Egypt	55.12	Japan	30.93*
U.K.	60.90*	U.K.	31.44*
Norway	65.19*	Canada	31.72*
Netherlands	65.54*	Switzerland	32.07*
Brazil	65.59	Germany, F.R.	32.44*
Turkey	66.72	Peru	32.53
Peru	66.91	Sweden	32.85*
Bangladesh	67.02	U.S.A.	33.06*
Finland	69.06**	New Zealand	33.75*
Spain	72.01**	Venezuela	33.84
Colombia	72.84	S. Africa	34.69
Pakistan	73.13	Italy	35.62*
Syria	73.29	Brazil	36.47
Sri Lanka	74.61	Denmark	37.31*
Denmark	74.96**	Yugoslavia	37.54
Switzerland	77.68**	Chile	39.24
Sweden	79.91**	Turkey	40.01
Austria	81.19**	France	40.25**
Taiwan	81.41	Netherlands	40.44**
Italy	82.46**	Bangladesh	40.89
Germany, F.R.	82.52**	Colombia	41.63
Canada	83.56**	Belgium	41.90**
Portugal	84.29	Syria	43.78
New Zealand	85.03**	Egypt	44.60
France	86.05**	Israel	45.36**
Mauritius	86.16	Philippines	48.04
U.S.A.	88.30**	Portugal	53.71
Israel	89.31**	Sri Lanka	59.03
Belgium	89.46**	Argentina	66.90
Australia	90.71**	Mauritius	88.66
Argentina	97.96	Taiwan	89.90
Average	68.30	Average	37.67

[1] An (*) to the right of the computed technical efficiency denotes developed countries below the computed average level of technical efficiency and (**) denotes developed countries above the average.

Also, the results show that the country ranking based on technical efficiency vary with the method of estimation used, i.e., deterministic or stochastic frontier functions. However, Kendall's Tau coefficient test (Gibbons and Chakraborti (1992)) indicated there is insufficient statistical evidence to claim an absence of association between the two rankings. The statistical test showed a positive relationship between the two country rankings.

Analyzing the results separately for developed and developing countries, we see that technical efficiencies for developed countries are higher than for developing countries for Model 1 but not necessarily for Model 2. The distribution of technical efficiencies for developing and developed countries are shown in Tables 6 and 7.

Table 6 Distribution of Technical Efficiencies for Developing Countries (Percentage of Sample)

	Model 1		Model 2	
Technical Efficiency	LP	ST	LP	ST
100%	0.00	0.00	0.00	0.00
90.0-99.9%	4.55	13.64	4.55	0.00
80.0-89.99%	13.64	4.55	13.64	9.09
70.0-79.99%	9.09	0.00	18.18	0.00
60.0-69.99%	22.73	13.64	18.18	4.55
50.0-59.99%	22.73	22.73	22.73	9.09
40.0-49.99%	13.64	27.27	13.64	27.27
30.0-39.99%	9.09	9.09	9.09	27.27
20.0-29.99%	4.55	9.09	0.00	13.64
10.0-19.99%			0.00	9.09
Average Efficiency (%)	61.43	55.46	62.40	42.86

Table 7 Distribution of Technical Efficiencies for Developed Countries (Percentage of Sample)

	Model 1		Model 2	
Technical Efficiency	LP	ST	LP	ST
100%	0.00	0.00	0.00	0.00
90.0-99.9%	9.52	0.00	4.76	0.00
80.0-89.99%	23.81	9.52	42.86	0.00
70.0-79.99%	23.81	9.52	19.05	0.00
60.0-69.99%	28.57	47.62	19.05	0.00
50.0-59.99%	4.76	23.81	4.76	0.00
40.0-49.99%	9.52	4.76	9.52	19.05
30.0-39.99%	0.00	4.76	0.00	47.62
20.0-29.99%			0.00	33.33
10.0-19.99%				
Average Efficiency (%)	72.39	63.18	74.52	32.23

Over 33% of the developed countries had technical efficiency measures over 80% in all models (other than ST models) while for developing countries less than 19% had over 80% (except ST model results). Average technical efficiencies are higher for developed countries as compared to developing countries (except for the stochastic estimates in Model 2). A t-test to compare means verified this result (at the 5% level of significance).

VII. Summary and Conclusions

The point of departure in this study, from previous studies on metaproduction functions, was the use of frontier metaproduction functions. Efficiency measurements are a natural extension of frontier production functions. While previous studies have estimated technical efficiencies based on metaproduction functions, they compare observed output with an average function. A methodological contribution of this research is the estimation of technical efficiencies based on deterministic and stochastic frontier metaproduction functions.

The estimated metaproduction functions indicate that labour has the largest contribution to agricultural output in both developed and developing countries. The results from the average and the deterministic frontier metaproduction functions suggest increasing returns to scale for conventional inputs for developed countries. However, when metaproduction functions were estimated as stochastic functions, no such phenomena was observed. In contrast, independent of the method of estimation, constant returns to scale were found for developing countries.

Many of the developed countries considered in this study have experienced changes in the structure of their agricultural holdings. Average farm size for countries such as the U.S., Australia, and New Zealand have increased over time. Furthermore, most of the developed countries already experienced out-migration of labour from agriculture to other economic sectors. During this process, labour was replaced with high levels of mechanization. The increase in fixed indivisible inputs (e.g., farm machinery and equipment) together with increasing farm sizes could account for the increasing returns to scale in developed countries.

Differences were seen in rank ordering of the 43 countries studied, depending on the metaproduction function used for comparison. However, these disparities were statistically insignificant, leading to the conclusion that there is a positive correlation between the rank ordering of deterministic and stochastic frontiers. Thus, when it is the relative technical efficiency among countries that is emphasized, potential flexibility exists in the selection of the form for the frontier production function, with insignificant impact on the final outcome.

In comparing the average technical efficiencies for stochastic and deterministic frontier metaproduction functions using similar groupings of data, it was seen that average technical efficiencies estimated through deterministic frontiers were higher than those from stochastic frontiers. This results from the stochastic frontier output level lying above the deterministic frontier output for a larger number of countries due to the effects of the random error component. These findings suggest that countries with low technical efficiencies (especially for certain developed countries) associated with the stochastic frontiers could be attributed to random disturbances or random events.

It was also observed that developed countries did not necessarily reach the highest efficiency levels, as a rule. However, the popular notion that developed countries in general are more efficient than developing countries was upheld by these research findings (with the exception of the stochastic estimates in Model 2). In another study, Frisvold and Lomax (1991), estimated total factor productivity for some of the countries included in this study. Their index was based on an average metaproduction function and was not fully comparable to the technical efficiencies measured in this study. Yet it is interesting to see that developing countries considered by those authors had fairly low factor productivity when compared to developed countries.

In general, results indicate agricultural productivity for developing countries on a per farm basis deteriorated over the time period under consideration. The opposite occurred for developed nations. Despite technical and biological advances made in agricultural sciences and later diffused to developing countries, an increasing productivity gap between developed and developing countries still exists. Similar conclusions were drawn in other studies based on average metaproduction functions estimated for the same data set (Trueblood (1991)).

While the results of this study point to widening productivity gaps between developing and developed countries across the time period studied, certain developing countries display a capacity to operate on the same frontier metaproduction function as the developed countries. The widening gap could be the result of differences in diffusion of technology across countries. Even if the technological advances made in developed countries are available to developing countries, modifications are often necessary to adjust to specific country situations. Also, infrastructure considerations such as transportation and communication in developing countries could prohibit optimal use of available technology Case studies or country specific studies are needed to investigate these differences in productivity and technological adoption.

Furthermore, government policies can have an impact on the performance of production units, For instance, in countries where agriculture is heavily subsidized (e.g., fertilizer subsidies), studies have found technical efficiencies to be low. The incentives to operate more efficiently and closer to the frontier tend to be weaker in countries with subsidies than without. However, subsidization of the research sector could result in the development of more applicable technology, which in turn improves efficiency. Hu and Antle (1993) found that agricultural policies adopted by individual countries have a significant effect on agricultural productivity. If an economy is severely distorted by government intervention, they concluded that marginal policy changes would not affect current productivity. In this light, a production frontier specification which includes policy variables would be better equipped to explain technical efficiency differentials.

An interesting extension of this work would be to explain the technical efficiency or inefficiency results found in this study. A two-step procedure is commonly used (see Kalirajan and Shand (1985), Ali and Flinn (1987) and Squires and Tabor (1991)) which involves estimating the technical efficiency/inefficiency measure via the stochastic frontier production function. Using the efficiency/inefficiency estimates from the first step, these values are regressed in the second step on a set of socio-economic variables (e.g., average education level, credit availability, employment rates, etc.).

Battese and Coelli (1995) used a modified version of FRONTIER Version 2.0 to estimate a simultaneous system of equations that explained technical inefficiencies of paddy farmers in India. The firm specific effects (U_{it}s) were estimated simultaneously along with the stochastic frontier production function. This approach is an improvement on the two-step method of explaining production (in)efficiencies. The current version of the software, FRONTIER Version 4.1, has this capability to specify U_{it} as an explicit function of a vector of environmental characteristics that are exogenously determined (Audibert (1997), Battese and Broca (1997), Coelli *et al*. (1999) and Taymaz and Saatci (1997)). Thus, there exists potential to extend the current study using either of the above approaches.

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