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THE META-PRODUCTION FUNCTION APPROACH TO TECHNOLOGICAL CHANGE IN WORLD AGRICULTURE*

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An alternative meta-production function for agriculture is estimated with the cross-section data for 43 countries and three years (1960, 1970 and 1980) constructed and used by Kawagoe, Hayami and Ruttan and Hayami and Ruttan in their studies. By allowing for country-specific efficiency factors and using a flexible functional form – the transcendental logarithmic production function – strikingly different results from those of Kawagoe, Hayami and Ruttan are obtained. In particular, it is found that elasticity of output with respect to machinery is variable and the degree of local returns to scale is not constant and increases with the usage of machinery.

1. Introduction

The point of departure of this study is the concept of a meta-production function, first introduced by Hayami (1969) and Hayami and Ruttan (1970, 1985). A production function is, by definition, a relationship between output and inputs. For a single country, say the ith, the production function may be written as

$$y_{it} = F_i(X_{i1t}, X_{i2t}, \ldots, X_{imt}, t) \tag{1}$$

where y_{it} is the quantity of output produced per producer unit and X_{ijt} is the quantity of the jth input employed per producer unit, $j = 1, \ldots, m$, in the ith country in the tth period. Note that the production function is subscripted by i, that is, individual country production functions may differ across countries.

There are, however, often difficulties associated with the estimation of

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individual country production functions from individual country data alone. The first difficulty is insufficient variation of the quantities of inputs, due to multicollinearity (e.g., capital and labor moving together), or due to restricted range of variation (e.g., arable land being more or less fixed), or due to approximate constancy of factor ratios resulting from approximate constancy of relative factor prices (possibly reflecting relative scarcities) within the country. Insufficient variation in the data due to any one of the above-mentioned reasons results in imprecision, unreliability, and possible under-identification of the estimated parameters of the production function. In addition, insufficient variation in the data implies a relatively restricted domain of applicability of the estimated production function because the behavior of the production function outside of the range of experience of the data is essentially unknown and any extrapolation is based on faith. Moreover, even if one is willing to assume that the same production function is valid outside the range of experience of the data, the confidence 'band' of the 'true' production function outside the range will become so 'wide' that it may be virtually useless.[1]

The second difficulty is the general inability of separate identification of the level of technological change of the production function of an individual country *and* its biases or the degree of returns to scale from time-series data on output and inputs *of that country alone*. For example, if output and inputs are both growing over time, it will be in general impossible to separately identify and estimate the technological change effect from the scale effect without making strong a priori assumptions.[2]

A meta-production function is defined as the common underlying production function that can be used to represent the input–output relationship of a given industry, e.g., agriculture, in *all* countries, i.e.,

$$y_{it} = F(X_{i1t}, \ldots, X_{imt}, t), \quad \forall i. \tag{2}$$

Note that the production function is no longer subscripted – it is the same for all i. The concept of a meta-production function is theoretically attractive because it is based on the simple but appealing hypothesis that all producers (countries) have potential access to the same technology but each may choose to operate on a different part of it depending on specific circumstances such as the qualities and quantities of the natural endowments, the structure of relative prices of the inputs, and the basic economic environ-

[1]The confidence band for a regression line is first derived by Working and Hotelling (1929). See also Miller (1981, pp. 109–128), for a discussion and an extension of the concept for a regression surface.

[2]Of course, if specific functional form assumptions are made, the scale effect and the technological change effect can be separately identified and estimated under appropriate conditions (but *not* for the Cobb–Douglas production function).

ment. It is empirically attractive because it justifies the pooling of data from different countries to estimate the common underlying production function, thus increasing both the ranges of variation of the independent variables and the total number of observations, and thereby reducing the possibility of multicollinearity, increasing the degree of reliability of the estimated production function and enlarging its domain of applicability. Moreover, a meta-production function can be estimated from intercountry data even when individual country production functions cannot be estimated from individual country data because of an insufficient number of observations.

It is straightforward to see that with greater ranges of variation of the inputs and a greater number of observations, the possibility of multicollinearity in the sample data may be reduced and the domain of applicability of the estimated production function is enlarged. But how do they increase the reliability of the estimated production function?

It turns out that the degree of reliability is increased in two ways. For a given algebraic functional form for the production function, the variance of the estimated coefficients decreases with increases in both the ranges of variation of the independent variables and the number of observations. Figs. 1 and 2 provide an illustration of how the range of variation of the independent variable affects the reliability of the estimated slope of a straight line. With a small range of variation as in fig. 1, any number of straight lines would have approximately the same statistical fit. Thus, the slope cannot be estimated with any precision. With a large range of variation as in fig. 2, the slope of the straight line can be estimated with much greater precision. Of course, increases in the number of observations, holding the range of variation constant, also increases the precision of the estimated parameters of the production function under the assumption that the model is correct.

In addition, the pooling of production data from different countries which overlap in time provides the opportunity of taking more than one look at the technology at any given point in time, thus making it potentially feasible to identify separately the degree of returns to scale and the level and biases of technological change and to test such hypotheses as the embodiment of technological change, neither of which is possible using data from only a single country.

However, while the use of pooled intercountry data in the estimation of the meta-production function opens up new opportunities, it also leads to new problems. The first problem is the non-comparability of data, caused by the possible existence of intercountry differences in the definitions, measurements, and qualities of the outputs and inputs. For example, in agriculture, the composition of output, say, between crops and livestock, may be very different across countries. The definition of a labor day may be different across countries. The intrinsic quality of a hectare of land may be different across countries and its actual efficiency may differ even further depending

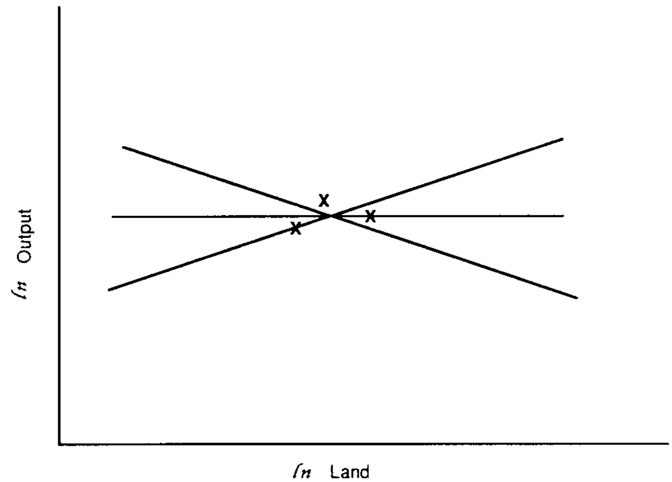

Fig. 1. Small range of variation.

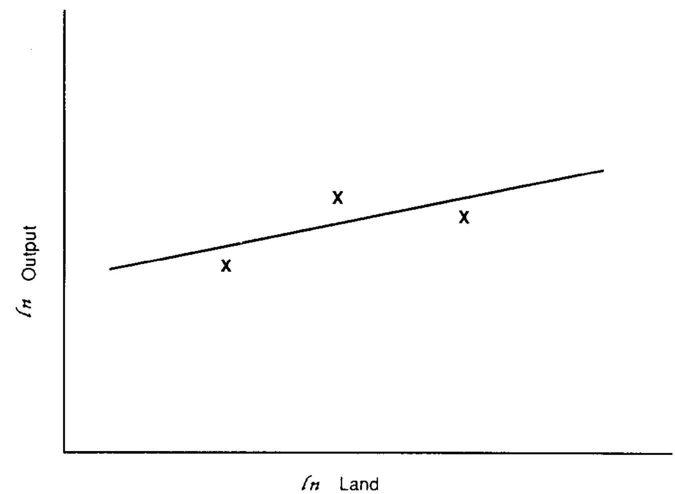

Fig. 2. Large range of variation.

on the availability of irrigation. However, even if it were possible to standardize the definitions, measurements and qualities of outputs and inputs across countries completely, the actual efficiencies of the inputs may still differ across countries because of a second problem – the existence of intercountry differences in the basic economic environment. They include differences in climate, topography and infrastructure broadly defined that are not generally reflected in the measured inputs, however standardized. They also include differences in the levels of technical efficiency, that is, the ability of producing outputs from given quantities of inputs, which may depend on institutional and organizational factors. The third problem is the extensiveness of the domain of the quantities of inputs over which an algebraic functional form chosen for the production function is expected to apply. When the ranges of variation of the inputs are large, it becomes less likely that a simple algebraic functional form such as the linear or the Cobb–Douglas (which is linear in the logarithms) production function will provide a satisfactory representation of the input–output relationship over the entire ranges. This situation is illustrated in figs. 3 and 4. In fig. 3, a straight line provides a reasonable approximation whereas in fig. 4 a straight line is clearly an unsatisfactory approximation.

If intercountry differences in either the measured inputs or the unmeasured (and possibly unmeasurable) environmental factors are ignored, the resulting estimated production function is likely to be biased. If a simple algebraic functional form for the production function is imposed on input data with wide ranges of variation, the resulting estimated production function is also likely to be biased. In this study we shall show how both types of biases may be reduced or eliminated through taking into account country-specific effects and using a flexible functional form.

2. The Kawagoe–Hayami–Ruttan meta-production function for world agriculture

Kawagoe, Hayami and Ruttan (1985) (hereinafter K-H-R) and Hayami and Ruttan (1985), following up on Hayami and Ruttan (1970), estimated an agricultural production function using intercountry data for three years – 1960, 1970 and 1980. However, in fact, the flow variables, such as output and fertilizer input, are averages of (1957–62), (1967–72) and (1975–80) respectively, whereas the stock variables, such as land, are the actual levels at 1960, 1970 and 1980 respectively. Outputs (y) are measured as gross outputs net of agricultural intermediate products such as feed and seeds and expressed in terms of wheat-equivalents or wheat units. Five conventional inputs, labor (X_1), land (X_2), livestock (X_3), fertilizer (X_4), and machinery (X_5), and two non-conventional inputs, general and technical education (X_6 and X_7), are distinguished.

Labor, land and livestock are measured, respectively, by the economically active male population in agriculture,[3] by hectares of agricultural land, and by equivalent livestock units. Similarly, fertilizer (commercial only) and

[3]To the extent that the ratio of male to female active population in agriculture varies across countries, the labor input is measured with error. However, as long as the ratio remains approximately constant over time for each country, its effect can be captured through country and input-specific efficiency factors as discussed below.

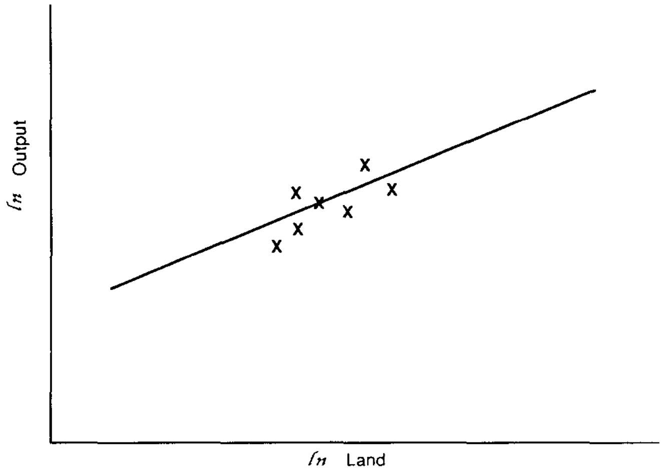

Fig. 3. Linear approximation adequate.

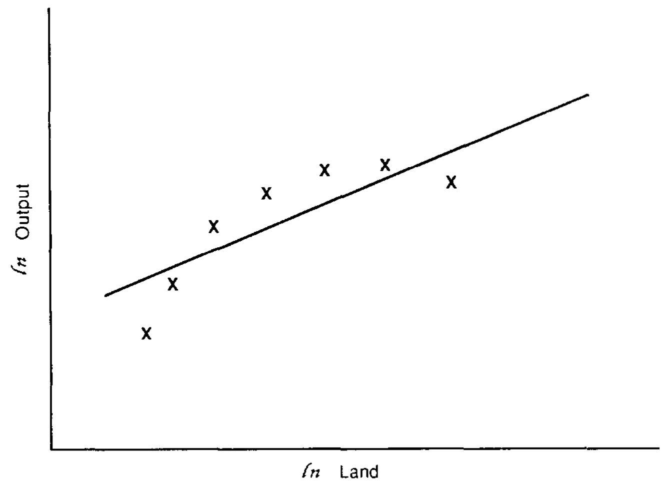

Fig. 4. Linear approximation inadequate.

machinery, are measured in equivalent nutrient (nitrogen, phosphorous and potash) units and tractor horsepower. General education is measured, alternately, by the literacy ratio and the school enrollment ratio (averaged over the immediately preceding decade) for the primary and secondary levels for the *entire* population, and not just for the agricultural population of each country. Technical education is measured by the number of agricultural graduates above the secondary level per ten thousand economically active male population in agriculture (again averaged over the immediately preceding decade). The sample of 43 countries is subdivided into two mutually exclusive and exhaustive subsamples: 22 LDC's and 21 DC's, with LDC's defined as countries with a 1980 per capita GNP below U.S. \$4,000 and DC's defined as countries with a 1980 per capita GNP above U.S. \$4,000. Libya, however, is included in the LDC subsample despite a 1980 per capita GNP in excess of U.S. \$8,000.[4] This classification strictly follows K-H-R. The data, carefully and meticulously constructed by Hayami and Ruttan (1985), have been made available in their Appendix A, where a detailed discussion of their construction is also included.[5]

The production function is estimated on a per-farm basis. The algebraic functional form chosen for the production function is the Cobb–Douglas form:

$$\ln y_{it} = \beta_0 + \sum_{j=1}^{7} \beta_j \ln X_{ijt} + \beta_8 DLDC_{it} + \beta_9 D1970_{it}$$

$$+ \beta_{10} D1980_{it} + \varepsilon_{it},$$

$$i = 1, \ldots, 43; \quad t = 1960,\ 1970,\ 1980. \tag{3}$$

where X_{i6t} is alternately represented by the literacy ratio or the school enrollment ratio; $DLDC_{it}$ is a dummy variable taking the value unity if the ith country is a less developed country and zero otherwise, $D1970_{it}$ and $D1980_{it}$ are each a dummy variable taking the value unity if the tth year is 1970 and 1980 respectively and zero otherwise. Note that β_9 and β_{10}, the coefficients of $D1970$ and $D1980$, may be interpreted as the technical progress that has occurred between 1960 and 1970 and between 1960 and 1980 respectively. ε_{it} is a stochastic disturbance term having the properties of $E(\varepsilon_{it}) = 0$, $V(\varepsilon_{it}) = \sigma^2$, $\forall i, t$ and $C(\varepsilon_{it}, \varepsilon_{i't'}) = 0$, $i \neq i'$, $t \neq t'$, $\forall i, i', t, t'$. It is assumed

[4]The resulting classification is as follows:
LDC's – Argentina, Bangladesh, Brazil, Chile, Columbia, Egypt, India, Libya, Mauritius, Mexico, Pakistan, Paraguay, Peru, Philippines, Portugal, South Africa, Sri Lanka, Syria, Taiwan, Turkey, Venezuela, Yugoslavia.
DC's – Australia, Austria, Belgium, Canada, Denmark, Finland, France, West Germany, Greece, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, U.K., U.S.

[5]Hayami and Ruttan (1985), Appendix A: Intercountry Cross-Section Data.

that the stochastic disturbance term is uncorrelated with the variables on the right-hand side of eq. (3), so that the ordinary least-squares estimator is unbiased and efficient.[6]

Implicit in eq. (3) are the assumptions that all the definitions, measurements and qualities of the factors of production are comparable across countries and that there exists no intercountry difference other than that represented by the LDC dummy variable.

We may observe that there exist considerable variations in the quantities of the inputs per farm across countries. In table 1 we present the minimum and maximum values observed for the quantities of each input in each year. The difference between the maximum and minimum ranges from 84 times for labor to 41,900 times for machinery – very wide ranges indeed. The factor ratios also vary greatly across countries – fertilizer and labor per hectare by a factor of 1,000 and machinery per hectare by a factor of 10,000.

What are the principal K-H-R findings? First, by estimating separate production functions by year, they found the production function to be stable over the entire period. Second, they found significant differences between the LDC's and the DC's: in particular, constant returns to scale in the agriculture of the LDC's and increasing returns to scale in the agriculture of the DC's. Third, they found that while the green revolution was the driving force behind technological change in the LDC's, the increased use of machinery was the driving force behind technological change in the DC's. The K-H-R ordinary least-squares estimates based on eq. (3) are presented in the first two columns of table 2 (all 43 countries), 3 (22 LDC's) and 4 (21 DC's).[7] K-H-R also estimated the production functions using the method of principal components. However, as these latter estimates are in general biased, we shall not discuss them here.

Despite a generally good statistical fit, the K-H-R estimates of several of the coefficients appear implausible. First, the estimated coefficients for land – 0.03 for all countries, -0.05 for LDC's and up to 0.10 for DC's – appear far too low, especially for the LDC's. Second, the estimated coefficients for the literacy ratio and the school enrollment ratio appear to be too high for the LDC's and to have the wrong sign for the DC's. Third, the estimated

[6]To the extent that the stochastic disturbance term represents *only* the effect of fluctuations of weather, it is unlikely to be correlated with the right-hand variables which are either stock variables or annual averages of flow variables. However, to the extent that it also represents country-specific effects, it may be correlated with the right-hand variables, and the ordinary least-squares estimator may no longer be unbiased or efficient unless account is taken of the country-specific effects.

[7]These results are not exactly the same as those presented in Kawagoe, Hayami and Ruttan (1985, p. 119) or Hayami and Ruttan (1985, p. 145) but are qualitatively similar. We were informed by Professor Yujiro Hayami that there were slight errors in their reported results for all countries and for less developed countries because of data discrepancies for Egypt and South Africa.

Table 1

Ranges of variation of quantities of inputs per farm.

Input	1960 Min.	1960 Max.	1970 Min.	1970 Max.	1980 Min.	1980 Max.	Maximum ratio of max. to min.
Labor (male workers)	0.5 (Norway)	13.5 (South Africa)	0.3 (Norway)	15.2 (South Africa)	0.3 (Norway)	25.2 (South Africa)	84.0
Land (hectares)	0.9 (Egypt)	1,850.0 (Australia)	0.9 (Egypt)	1,980.0 (Australia)	0.8 (Egypt)	2,220.0 (Australia)	2,775.0
Livestock (heads)	0.8 (Japan)	141.0 (South Africa)	1.2 (Taiwan)	200.0 (New Zealand)	1.4 (Egypt)	220.0 (South Africa)	176.0
Fertilizer (metric tons)	0.003 (Bangladesh)	3.4 (New Zealand)	0.02 (Bangladesh)	6.5 (New Zealand)	0.001 (Paraguay)	12.3 (South Africa)	1,230.0
Machinery (horsepower)	0.001 (Bangladesh)	41.9 (U.S.A.)	0.007 (Bangladesh)	88.8 (South Africa)	0.015 (Bangladesh)	127.8 (Canada)	41,900.0

Table 2

Estimates of the intercountry production function (all 43 countries).[a]

Regression	Re-estimated Kawagoe–Hayami–Ruttan (with literacy)	Re-estimated Kawagoe–Hayami–Ruttan (with enrollment)	Transformed first-difference (with literacy)	Transformed first-difference (with enrollment)	Transformed first-difference (without literacy and enrollment)
Constant	1.905 (4.788)	1.814 (3.394)	–	–	–
Labor (L)	0.560 (7.988)	0.555 (7.910)	0.162 (2.314)	0.192 (2.954)	0.325 (4.333)
Land (A)	0.035 (1.011)	0.032 (0.919)	0.938 (9.164)	0.939 (9.081)	0.668 (5.793)
Livestock (S)	0.293 (6.302)	0.299 (6.373)	0.133 (2.162)	0.149 (2.429)	0.134 (2.249)
Fertilizer (F)	0.154 (4.010)	0.150 (3.852)	0.023 (0.840)	0.012 (0.383)	0.057 (2.173)
Machinery (M)	0.070 (1.998)	0.076 (2.186)	0.058 (2.555)	0.062 (2.701)	0.061 (2.751)
Literacy ratio (E)	0.123 (1.379)	–	0.187 (1.683)	–	–
School enrollment ratio (E)	–	0.149 (1.186)	–	0.187 (1.628)	–
Technical education (T)	0.181 (6.025)	0.176 (5.629)	0.059 (2.281)	0.058 (2.213)	0.095 (3.816)
LDC dummy	−0.461 (4.224)	−0.465 (4.249)	–	–	–
Time dummy 1970	−0.002 (0.023)	−0.016 (0.232)	0.120 (3.206)	0.112 (2.969)	0.170 (3.948)
Time dummy 1980	−0.041 (0.512)	−0.064 (0.801)	0.193 (3.215)	0.178 (2.941)	0.270 (4.164)
LDC* 1970 dummy	–	–	–	–	−0.103 (2.261)
LDC* 1980 dummy	–	–	–	–	−0.175 (2.768)
$\bar{R}^2$	0.946	0.945	0.829	0.829	0.837
S	0.287	0.287	0.124	0.124	0.121

[a]Numbers in parentheses are t-ratios.

coefficients for the year dummies, which represent technological change, are negative (albeit statistically insignificant) for all countries and very large negative and statistically significant for the LDC's. However, it seems extremely unlikely that the level of the agricultural technology for the LDC's could have retrogressed by 15–20% over the decade of the 1960's and 30–40% over the two decades of the 1960's and 1970's.

Table 3

Estimates of the intercountry production function (22 less developed countries).[a]

Regression	Re-estimated Kawagoe–Hayami–Ruttan (with literacy)	Re-estimated Kawagoe–Hayami–Ruttan (with enrollment)	Transformed first-difference (with literacy)	Transformed first-difference (with enrollment)	Transformed first-difference (without literacy and enrollment)
Constant	1.113 (2.276)	0.666 (1.043)	–	–	–
Labor (L)	0.672 (6.068)	0.633 (5.898)	0.268 (2.469)	0.332 (3.115)	0.349 (3.247)
Land (A)	−0.051 (0.821)	−0.064 (1.050)	0.891 (5.741)	0.864 (5.357)	0.796 (5.062)
Livestock (S)	0.264 (3.033)	0.303 (3.617)	0.053 (0.638)	0.094 (1.123)	0.088 (1.038)
Fertilizer (F)	0.081 (1.461)	0.083 (1.495)	0.042 (1.307)	0.023 (0.563)	0.058 (1.796)
Machinery (M)	0.141 (2.761)	0.145 (2.863)	0.044 (1.631)	0.057 (1.939)	0.042 (1.505)
Literacy ratio (E)	0.268 (2.498)	–	0.282 (2.230)	–	–
School enrollment ratio (E)	–	0.391 (2.589)	–	0.248 (1.486)	–
Technical education (T)	0.177 (4.507)	0.165 (4.097)	0.071 (2.222)	0.072 (2.099)	0.094 (2.941)
LDC dummy	–	–	–	–	–
Time dummy 1970	−0.157 (1.550)	−0.218 (2.132)	0.071 (1.422)	0.056 (1.017)	0.090 (1.765)
Time dummy 1980	−0.328 (2.762)	−0.421 (3.514)	0.125 (1.600)	0.098 (1.145)	0.144 (1.760)
$\bar{R}^2$	0.919	0.919	0.834	0.822	0.816
S	0.307	0.306	0.129	0.133	0.136

[a]Numbers in parentheses are t-ratios.

It should be added that a low estimated production elasticity for land is not uncommon for production functions estimated from intercountry data. Among the studies summarized by Kawagoe, Hayami and Ruttan (1985, p. 123, Table 3) and Hayami and Ruttan (1985), only one, Bhattacharjee (1955) has an estimated coefficient for land that exceeds 0.20.[8] This is, however, inconsistent with cross-sectional empirical evidence based on individual farm-level data.[9]

[8]The other studies included are Antle (1983), Hayami (1969), Hayami and Ruttan (1970), Evenson and Kislev (1975), Mundlak and Hellinghausen (1982), Nguyen (1979) and Yamada and Ruttan (1980). See also Scandizzo (1984).

[9]See, for example, the summaries and surveys in Heady and Dillon (1961), Jamison and Lau (1982) and Lau and Yotopoulos (1979).

Table 4

Estimates of the intercountry production function (21 developed countries).[a]

Regression	Re-estimated Kawagoe–Hayami–Ruttan (with literacy)	Re-estimated Kawagoe–Hayami–Ruttan (with enrollment)	Transformed first-difference (with literacy)	Transformed first-difference (with enrollment)	Transformed first-difference (without literacy and enrollment)
Constant	9.592 (2.768)	3.110 (2.651)	–	–	–
Labor (L)	0.660 (7.995)	0.709 (8.676)	0.229 (2.022)	0.317 (2.918)	0.322 (2.827)
Land (A)	0.069 (2.116)	0.100 (3.221)	0.383 (2.057)	0.314 (1.725)	0.217 (1.170)
Livestock (S)	0.186 (2.865)	0.147 (2.169)	0.326 (3.495)	0.294 (3.198)	0.255 (2.693)
Fertilizer (F)	0.192 (2.481)	0.191 (2.317)	0.100 (1.342)	0.096 (1.236)	0.154 (2.014)
Machinery (M)	0.215 (3.838)	0.175 (3.219)	0.041 (0.798)	0.066 (1.372)	0.127 (3.204)
Literacy ratio (E)	−1.600 (2.090)	–	2.756 (2.423)	–	–
School enrollment ratio (E)	–	−0.173 (0.650)	–	0.465 (2.119)	–
Technical education (T)	0.134 (3.907)	0.142 (3.698)	0.047 (0.839)	0.109 (2.247)	0.120 (2.370)
LDC dummy	–	–	–	–	–
Time dummy 1970	0.044 (0.639)	0.089 (1.308)	0.143 (1.755)	0.111 (1.409)	0.056 (0.715)
Time dummy 1980	0.095 (1.086)	0.172 (2.126)	0.243 (1.772)	0.165 (1.280)	0.096 (0.729)
$\bar{R}^2$	0.965	0.963	0.816	0.809	0.789
S	0.178	0.184	0.091	0.093	0.098

[a]Numbers in parentheses are t-ratios.

The estimated coefficients for the literacy ratio and the school enrollment ratio are probably unreliable because the variables themselves pertain to the entire population rather than just the agricultural population or labor force. Moreover, these ratios for most of the DC's are close to unity with only a few exceptions. The implausibly large, negative and statistically significant estimated coefficient for the DC's, 1.60, must be regarded as spurious. These problems with the general education variables have also been pointed out by K-H-R.

3. A Cobb–Douglas meta-production function with country-specific effects

We generalize the K-H-R meta-production function by allowing country-specific effects. The country-specific effects are introduced in two ways. First, we assume that there are differences in the levels of technical efficiency across countries, so that even if the quantities of all inputs, appropriately standardized, are the same, the quantities of outputs, also appropriately standardized, may still differ. Of course, the differences in the levels of technical efficiency may also reflect differences in the basic economic environment, such as climate, topography, infrastructure and institutions. Second, we assume that the factors of production, including both the physical inputs and the education variables, are not directly comparable, or 'efficiency-equivalent', across countries, even with the standardizations, as measured. Instead, we assume that they are comparable across countries only after the multiplication of the quantity of each factor by a constant country and factor-specific scalar conversion factor, called an efficiency factor.[10] For example, we do not assume that one hectare of land in Japan is equivalent in efficiency to one hectare of land in the United States, but we assume that they may be converted into each other through the multiplication of constant conversion factors, such as one hectare of land in Japan for every two hectares of land in the United States.[11] In this case, the efficiency factor of Japanese land may be taken to be 2 and the efficiency factor of U.S. land to be 1. In general, for each country, the quantity of each *efficiency-equivalent* input is given by

$$X^*_{ijt} = A_{ij} X_{ijt},$$

$$i=1,\dots,43, \quad j=1,\dots,7, \quad t=1960,\ 1970,\ 1980. \tag{4}$$

where the A_{ij}'s are unknown and unobserved constant efficiency factors and X_{ijt}'s are the *measured* quantities of inputs per farm and educational variables of the ith country in the tth year.

The meta-production function is assumed to apply to all countries only in terms of efficiency-equivalent quantities of outputs and inputs, i.e.,

$$y_{it} = A_{i0} F(X^*_{i1t}, X^*_{i2t}, \dots, X^*_{imt}, t), \tag{5}$$

where A_{i0} is the level of technical efficiency of the ith country in agricultural production, and not necessarily in terms of the measured quantities of

[10] It is also called an augmentation factor.

[11] There is, of course, no reason why the efficiency factors are constant over time. With a sufficiently long time-series of cross-sections, even time-varying efficiency factors can be identified and estimated. In this study, however, there are too few time periods to allow time-varying efficiency factors.

outputs and inputs.[12] In terms of the measured quantities of outputs and inputs, the meta-production function takes the form

$$y_{it}=A_{i0}F(A_{i1}X_{i1t},\ A_{i2}X_{i2t},\dots,A_{im}X_{imt},t). \tag{6}$$

For the empirical estimation of our meta-production function we first maintain the hypothesis that it has the Cobb–Douglas form as in eq. (3) and introduce a stochastic disturbance term, ε_{it}. Thus:

$$\begin{aligned}\ln y_{it}&=\beta_0+\ln A_{i0}+\sum_{j=1}^{7}\beta_j\ln X^*_{ijt}+\beta_8 DLDC_{it}\\&\quad+\beta_9 D1970_{it}+\beta_{10}D1980_{it}+\varepsilon_{it},\\ i&=1,\dots,43,\quad t=1960,1970,1980.\end{aligned}\tag{7}$$

By using eq. (4), eq. (7) may be rewritten as

$$\begin{aligned}\ln y_{it}&=\beta_0+\ln A_{i0}+\sum_{j=1}^{7}\beta_j\ln A_{ij}+\beta_8 DLDC_{it}+\sum_{j=1}^{7}\beta_j\ln X_{ijt}\\&\quad+\beta_9 D1970_{it}+\beta_{10}D1980_{it}+\varepsilon_{it},\end{aligned}\tag{8}$$

which may be further rewritten as

$$\begin{aligned}\ln y_{it}&=\ln A^*_i+\sum_{j=1}^{7}\beta_j\ln X_{ijt}+\beta_9 D1970_{it}+\beta_{10}D1980_{it}+\varepsilon_{it},\\ i&=1,\dots,43,\quad t=1960,1970,1980.\end{aligned}\tag{9}$$

Note that eq. (9) depends only on the measured quantities of output and the factors. However, there is now a constant term, $\ln A^*_i$, which varies across countries. It is assumed that the stochastic disturbance term is uncorrelated with the variables on the right-hand side of eq. (9). This is plausible, despite the fact that the quantity of planned output and the quantities of inputs are probably simultaneously determined, because the major component of the

[12]Note that the differences in the levels of technical efficiency across countries are assumed to be neutral. Note also that without loss of generality one may take the A_{i0} and A_{ij}'s for one country to be identical unities.

stochastic disturbance term is due to fluctuations in the weather, which are unlikely to be correlated with the quantities of inputs. In addition, the quantities of inputs are measured mostly as potential or stock variables, rather than actual current flow variables. Finally, the stochastic disturbance term may be correlated with the right-hand variables because of a common country effect. However, this is taken into account by the inclusion of country-specific dummy variables in the production function in eq. (9).[13]

Under our assumptions, we can estimate eq. (9) directly by ordinary least-squares. However, it requires that we introduce 43 additional country-specific dummy variables for the $\ln A_i^*$'s. Instead, since we have three observations per country, we take first differences of each country to obtain

$$\begin{aligned}\ln y_{it}-\ln y_{i(t-1)}= & \sum_{j=1}^{7} \beta_j(\ln X_{ijt}-\ln X_{ij(t-1)}) \\ & +\beta_9(D1970_{it}-D1970_{i(t-1)}) \\ & +\beta_{10}(D1980_{it}-D1980_{i(t-1)})+\varepsilon_{it}-\varepsilon_{i(t-1)}, \\ i=1,\ldots,43, \quad & t=1970,\ 1980. \end{aligned} \tag{10}$$

The unknown $\ln A_i^*$'s are thus eliminated.[14]

If it were believed that the rate of technological change may differ systematically between LDC's and DC's, one may add two additional interaction terms to eq. (10), obtaining

$$\begin{aligned}\ln y_{it}-\ln y_{i(t-1)}= & \sum_{j=1}^{7} \beta_j(\ln X_{ijt}-\ln X_{ij(t-1)}) \\ & +\beta_9(D1970_{it}-D1970_{i(t-1)}) \\ & +\beta_{10}(D1980_{it}-D1980_{i(t-1)}) \\ & +\beta_{11} DLDC_{it}^*(D1970_{it}-D1970_{i(t-1)}) \end{aligned}$$

[13]Given the presence of the country-specific effects, the assumption that successive stochastic disturbance terms, reflecting primarily fluctuations in weather, are uncorrelated also becomes more plausible. The presence of the country-specific effects and the logarithmic transformation of output per farm also partially justify the assumption that the variance of the stochastic disturbance term in eq. (9) is identical across countries.

[14]Estimates of these $\ln A_i^*$'s can in fact be recovered and are the subject of another paper, Lau and Yotopoulos (1988).

$$+\beta_{12}DLDC_{it}^{*}(D1980_{it}-D1980_{i(t-1)})+\varepsilon_{it}-\varepsilon_{i(t-1)},$$

$$i=1,\ldots,43, \quad t=1970,1980. \tag{11}$$

While first-differencing removes the fixed country-specific effects, it introduces heteroscedasticity even if it is assumed to be absent prior to first-differencing. The stochastic disturbance term of eq. (11) takes the form of $\varepsilon_{it}-\varepsilon_{i(t-1)}$, so that successive stochastic disturbance terms are correlated. In fact their covariance is given by

$$C(\varepsilon_{it}-\varepsilon_{i(t-1)},\ \varepsilon_{i(t+1)}-\varepsilon_{it})=-V(\varepsilon_{it})=-\sigma^2,$$

which is no longer equal to zero. The variance of the first-differenced stochastic disturbance terms is given by

$$V(\varepsilon_{it}-\varepsilon_{i(t-1)})=2\sigma^2.$$

As the stochastic disturbance terms are no longer homoscedastic, the ordinary least-squares estimator is not the best linear and unbiased estimator for eq. (11). We can, however, transform the first-differenced equations further to obtain a specification that is homoscedastic. The transformation takes the following form:

$$\ln y_{i1970}-\ln y_{i1960}=\sum_{j=1}^{7}\beta_j(\ln X_{ij1970}-\ln X_{ij1960})$$

$$+\beta_9+\beta_{11}DLDC_{i1970}+\varepsilon_{i1970}-\varepsilon_{i1960},$$

$$i=1,\ldots,43; \tag{12}$$

$$(\ln y_{i1970}-\ln y_{i1960})/\sqrt{3}+2(\ln y_{i1980}-\ln y_{i1970})/\sqrt{3}$$

$$=\sum_{j=1}^{7}\beta_j[(\ln X_{ij1970}-\ln X_{ij1960})/\sqrt{3}+2(\ln X_{ij1980}-\ln X_{ij1970})/\sqrt{3}]$$

$$+\beta_9[1/\sqrt{3}-2/\sqrt{3}]+\beta_{10}[2/\sqrt{3}]$$

$$+\beta_{11}[DLDC_{i1970}/\sqrt{3}-2DLDC_{i1980}/\sqrt{3}]$$

$$+\beta_{12}[2DLDC_{i1980}/\sqrt{3}]+(\varepsilon_{i1970}-\varepsilon_{i1960})/\sqrt{3}$$

$$+2(\varepsilon_{i1980}-\varepsilon_{i1970})/\sqrt{3},$$

$$i=1,\ldots,43. \tag{13}$$

It may be verified that the variances of the stochastic disturbance terms in eqs. (12) and (13) are identical and that their covariance is zero. We conclude that the ordinary least-squares estimator applied to the *transformed* first-differenced specification in eqs. (12) and (13) is the best linear and unbiased estimator.[15]

4. Results of the transformed first-differenced Cobb–Douglas model

The results of the estimation of the transformed first-differenced model of eqs. (12) and (13) are presented in the third and fourth columns of tables 2, 3 and 4.[16] The differences between these results and the re-estimated K-H-R results are most striking, suggesting that the latter estimates may have been biased.[17] The estimated coefficients for land become much larger and statistically significant (although probably too large for all countries and for the LDC's). The estimates of the technological change coefficients now have the expected signs. However, the estimated coefficients for general education still appear unreasonably large. We conclude that the general education variables as defined and measured are unsatisfactory. We dropped the general education variables and reestimated, the results of which are reported in the fifth columns of tables 2, 3 and 4. The estimated coefficients in the fifth columns seem reasonable and consistent with a priori expectations. In particular, the estimated technological change coefficients are positive for both even though they are higher for the DC's than for the LDC's.

By estimating both eqs. (3) and (9) for all observations we can use the sums of squared residuals to test the hypothesis of non-existence of the country-specific effects other than the LDC effect. In other words, the null hypothesis is:

$$\ln A_i^* = \begin{cases} \ln A_{\mathrm{L}}^*, & \text{if the } i\text{th country is an LDC} \\ \ln A_{\mathrm{D}}^*, & \text{if the } i\text{th country is a DC.} \end{cases}$$

[15]Note that ordinary least-squares applied to the transformed first-differenced model is equivalent to ordinary least-squares applied to eq. (9). Thus, the first-differencing and transformation should be viewed simply as a procedure for facilitating the actual computation.

[16]As pointed out to us by Zvi Griliches in private correspondence, these estimates may be interpreted as the 'within' estimates in contradistinction to the 'total' estimates reported in the first and second columns of tables 2, 3 and 4.

[17]The failure to take into account the possible presence of country-specific effects in the context of this model implies that the variables may be measured with error. Griliches (1979, p. S37) has pointed out that 'modest error levels can account for much of the observed difference between total and within [estimates]'.

Table 5

Tests of non-existence of country-specific effects.

	Critical value at 5%	Re-estimated Kawagoe–Hayami–Ruttan (with literacy)	Re-estimated Kawagoe–Hayami–Ruttan (with enrollment)
All 43 countries	$F_{0.05}(41,77)$ $=1.54$	$F(41,77)$ $=29.1$	$F(41,77)$ $=29.1$
22 LDC's	$F_{0.05}(21,35)$ $=1.86$	$F(21,35)$ $=28.6$	$F(21,35)$ $=26.3$
21 DC's	$F_{0.05}(20,33)$ $=1.90$	$F(20,33)$ $=18.4$	$F(20,33)$ $=19.2$

Table 6

Tests of equality between less developed and developed countries.

Re-estimated Kawagoe–Hayami–Ruttan (with literacy)	Re-estimated Kawagoe–Hayami–Ruttan (with enrollment)	Transformed first-difference (with literacy)	Transformed first-difference (with enrollment)	Transformed first-difference (without literacy and enrollment)
$F(9,109)$ $=4.788$	$F(9,109)$ $=4.653$	$F(9,68)$ $=2.833$	$F(9,68)$ $=2.247$	$F(6,70)$ $=1.385$
$F_{0.05}(9,109)$ $=2.76$	$F_{0.05}(9,109)$ $=2.76$	$F_{0.05}(9,68)$ $=2.78$	$F_{0.05}(9,68)$ $=2.78$	$F_{0.05}(6,70)$ $=3.73$

The test statistics are reported in table 5. The hypothesis of non-existence of country-specific effects is decisively rejected. The hypotheses of non-existence of country-specific effects for the LDC's and DC's separately are also rejected.

Next, we test the hypothesis of whether the LDC's and the DC's have the same identical Cobb-Douglas production function up to a neutral scalar multiplicative factor. Based on the sum of squared residuals of eq. (3), which maintains the hypothesis of no country-specific effects, the hypothesis of identical production functions is rejected at the 5 percent level of significance. However, using the transformed first-differenced model of eq. (10), the hypothesis is barely rejected when the literary ratio is used as the general education variable and not rejected when the school enrollment ratio is used as the general education variable. When the general education variable is omitted, and the technological change coefficients are allowed to differ between LDC's and DC's, the hypothesis of identical production functions cannot be rejected at the 5 percent level of significance. These results are reported in table 6.

Finally, we examine the hypothesis of constant returns to scale. The Cobb–Douglas production function is characterized by fixed returns to scale.

K-H-R found evidence in favor of constant returns to scale for the LDC's and increasing returns to scale for the DC's. (See the first two columns of table 7.) However, when the transformed first-differenced model is used, the conclusions are exactly reversed. When the general education variable is omitted, the hypothesis of constant returns to scale is rejected for both the LDC's and the DC's at the 5 percent level of significance. These results are summarized in table 7.

5. The transcendental logarithmic meta-production function with country-specific effects

The estimation results of the transformed first-differenced Cobb–Douglas model (the fifth columns of tables 2, 3 and 4), while more plausible than the K-H-R results, are not completely satisfactory because of the relatively high estimated production elasticity for land for all countries and for the LDC's. It is suspected that the estimate may have been biased upward because of the omission of second-order terms (e.g. there is a high correlation not only between ln *Land* per farm and ln *Machinery* per farm but also between ln *Land* per farm and ln *Machinery* per farm squared). We next explore the possibility that the Cobb–Douglas production function is not sufficiently flexible to represent the meta-production function technology over these wide ranges of the quantities of inputs. For this purpose, we use the transcendental logarithmic production function introduced by Christensen, Jorgenson and Lau (1973), which also allows non-neutral scale effects, evidence for which was presented by K-H-R.[18] The transcendental logarithmic production function with neutral differences in the levels of technical efficiency may be written in terms of quantities of 'efficiency-equivalent' inputs and other factors as

$$\begin{aligned} \ln y_{it} = {} & \beta_0 + \ln A_{i0} + \sum_{j=1}^{7} \beta_j \ln X^*_{ijt} \\ & + \frac{1}{2} \sum_{j=1}^{5} \sum_{k=1}^{5} \delta_{jk} (\ln X^*_{ijt})(\ln X^*_{ikt}) \\ & + \beta_8 DLDC_{it} + \beta_9 D1970_{it} + \beta_{10} D1980_{it} + \varepsilon_{it}, \\ & i = 1, \ldots, 43, \quad t = 1960, 1970, 1980, \end{aligned} \tag{14}$$

where the A_{i0}'s are the neutral levels of technical efficiency, the X^*_{ijt}'s are the

[18] It should be added that K-H-R also estimated a transcendental logarithmic production function specification with the original data but found the results unsatisfactory.

Table 7

Estimates of the degree of returns to scale[a]

Regression	Re-estimated Kawagoe–Hayami Ruttan (with literacy)	Re-estimated Kawagoe–Hayami Ruttan (with enrollment)	Transformed first-difference (with literacy)	Transformed first-difference (with enrollment)	Transformed first-difference (without literacy and enrollment)
All countries	1.112	1.112	1.314	1.354	1.245
	(2.246)	(2.239)	(3.898)	(4.213)	(2.966)
	[1.980]	[1.980]	[1.994]	[1.994]	[1.994]
Less developed countries	1.107	1.100	1.298	1.370	1.333
	(1.714)	(1.597)	(2.749)	(3.276)	(2.985)
	[2.005]	[2.005]	[2.032]	[2.032]	[2.029]
Developed countries	1.322	1.322	1.079	1.090	1.075
	(4.603)	(4.424)	(0.663)	(0.506)	(2.239)
	[2.010]	[2.010]	[2.036]	[2.036]	[2.033]

[a]Numbers in parentheses are t-ratios for the null hypothesis of constant returns to scale. Numbers in square brackets are the critical values of the t-statistics at the 5 percent level of significance.

quantities of efficiency-equivalent inputs as defined in eq. (4), and the matrix $[\delta_{jk}]$ is without loss of generality taken to be symmetric. Eq. (14) may be rewritten in terms of the measured quantities of inputs and other factors as

$$\ln y_{it} = \ln A_i^* + \sum_{j=1}^{7} \beta_j \ln X_{ijt} + \frac{1}{2} \sum_{j=1}^{5} \sum_{k=1}^{5} \delta_{jk} \ln X_{ijt} \ln X_{ikt}$$

$$+ \beta_9 D1970_{it} + \beta_{10} D1980_{it} + \sum_{j=1}^{5} \beta_{ij}^* \ln X_{ijt} + \varepsilon_{it}, \tag{15}$$

where $\ln A_i^*$ and β_{ij}^*'s for each i are unknown constants that are functions of the β_j's, δ_{jk}'s, A_{i0} and A_{ij}'s. We note that first-differencing will only eliminate $\ln A_i^*$ but not the β_{ij}^*'s. However, as there are only three observations per country, it is not possible to identify the individual β_{ij}^*'s without making some strong assumptions. We make the assumption that

$$\beta_{ij}^* = \begin{cases} \beta_j^*, & \text{if the } i\text{th country is an LDC} \\ 0, & \text{if the } i\text{th country is a DC.} \end{cases}$$

With this assumption, and further allowing β_6, β_7, β_9 and β_{10} to differ between the LDC's and DC's, we obtain

$$\ln y_{it} = \ln A_i^* + \sum_{j=1}^{5} \beta_j \ln X_{ijt} + \sum_{j=1}^{5} \beta_j^* (DLDC_{it}^* \ln X_{ijt})$$

$$+ \beta_6 \ln X_{i6t} + \beta_6^* (DLDC_{it}^* \ln X_{i6t})$$

$$+ \beta_7 \ln X_{i7t} + \beta_7^* (DLDC_{it}^* \ln X_{i7t})$$

$$+ \frac{1}{2} \sum_{j=1}^{5} \sum_{k=1}^{5} \delta_{jk} \ln X_{ijt} \ln X_{ikt}$$

$$+ \beta_9 D1970_{it} + \beta_9^* (DLDC_{it}^* D1970_{it})$$

$$+ \beta_{10} D1980_{it} + \beta_{10}^* (DLDC_{it}^* D1980_{it}) + \varepsilon_{it},$$

$$i = 1, \ldots, 43; \quad t = 1960, 1970, 1980. \tag{16}$$

As before, by taking first differences of eq. (16) for each country, we eliminate the $\ln A_i^*$'s. We also further transform the first-differenced equation to achieve homoscedasticity. As the general education variables are unsatis-

Table 8

Tests of the transcendental logarithmic specification.

Hypothesis	Degrees of freedom	F-value	Critical value at 5%
1. Zero second-order parameters (Cobb–Douglas specification)	15, 55	2.35	1.86
2. Identical first-order LDC and DC parameters	6, 55	2.02	2.27
3. Additivity	10, 55	1.81	2.00

factory in terms of their definitions and measurements, we omitted them from the empirical analysis.

6. The results of the transformed, first-differenced, transcendental logarithmic model

The first hypothesis that we test is whether the Cobb–Douglas specification is adequate. This translates into the hypothesis that all the second-order coefficients, δ_{jk}'s, are zero. This hypothesis is rejected at the 5 percent level of significance. The second hypothesis that we test is whether the first-order coefficients, β_j's, are identical between the LDC's and the DC's, that is, whether β_j^*'s are zero. This hypothesis cannot be rejected at the 5 percent level of significance. The third hypothesis that we test is whether the transcendental logarithmic function is additive in the inputs, that is, has all second-order cross coefficients, δ_{jk}'s, $j \neq k$, equal to zero. This hypothesis cannot be rejected at the 5 percent level of significance. The results are summarized in table 8.

Normally, we would terminate our analysis here and adopt the additive transcendental logarithmic specification provisionally. However, we observe that the estimated second-order coefficients for the additive 'translog' specification with identical first-order LDC and DC coefficients still have very large estimated standard errors. We therefore proceed to test, for each input, the hypothesis that the second-order own coefficient, δ_{jj}, is equal to zero. It is clear from the sums of squared residuals that the only such hypothesis that can be rejected is that for machinery. We therefore estimated a final summary specification imposing this restriction for all inputs other than machinery. In any case, the values of the estimated coefficients do not appear sensitive to the specification chosen. The results of the estimation of the transcendental logarithmic function are reported in table 9.

The final summary specification is quite interesting. It implies the production function

Table 9

Estimates of the intercountry production function from transformed first-differenced data – transcendental logarithmic specifications (all 43 countries).[a]

	Additivity	Labor (L)	Land (A)	Livestock (S)	Fertilizer (F)	Machinery (M)	Summary
Specification							
Labor (L)	0.420	0.416	0.405	0.406	0.409	0.305	0.396
	(5.022)	(5.21)	(5.168)	(5.323)	(5.109)	(3.787)	(5.638)
Land (A)	0.335	0.343	0.419	0.357	0.359	0.713	0.403
	(1.610)	(1.708)	(3.092)	(1.790)	(1.790)	(3.899)	(3.282)
Livestock (S)	0.162	0.160	0.148	0.138	0.166	0.139	0.143
	(1.947)	(1.953)	(1.882)	(2.402)	(2.013)	(1.582)	(2.634)
Fertilizer (F)	0.029	0.029	0.049	0.031	0.055	0.156	0.058
	(0.452)	(0.461)	(0.972)	(0.500)	(2.088)	(2.966)	(2.455)
Machinery (M)	0.112	0.111	0.108	0.112	0.111	0.074	0.109
	(4.377)	(4.491)	(4.401)	(4.411)	(4.377)	(3.064)	(4.683)
Technical education (T)	0.114	0.115	0.110	0.113	0.110	0.086	0.108
	(4.352)	(4.440)	(4.425)	(4.362)	(4.508)	(3.265)	(4.714)
ln L-squared/2	−0.011	–	0.001	−0.004	−0.012	0.034	–
	(0.168)		(0.024)	(0.077)	(0.190)	(0.499)	

Table 9 (continued)

	Additivity	Labor (L)	Land (A)	Livestock (S)	Fertilizer (F)	Machinery (M)	Summary
ln A-squared/2	0.033 (0.538)	0.030 (0.515)	–	0.020 (0.389)	0.018 (0.349)	−0.079 (1.463)	–
ln S-squared/2	−0.017 (0.405)	−0.016 (0.380)	−0.006 (0.156)	–	−0.016 (0.373)	0.014 (0.329)	–
ln F-squared/2	−0.008 (0.472)	−0.008 (0.483)	−0.003 (0.233)	−0.007 (0.445)	–	0.027 (1.986)	–
ln M-squared/2	0.030 (3.235)	0.030 (3.297)	0.027 (3.567)	0.029 (3.248)	0.027 (3.856)	–	0.026 (4.137)
Time dummy 1970	0.114 (2.246)	0.110 (2.260)	0.105 (2.192)	0.106 (2.226)	0.101 (2.251)	0.108 (2.060)	0.098 (2.307)
Time dummy 1980	0.171 (2.291)	0.171 (2.302)	0.164 (2.241)	0.163 (2.278)	0.159 (2.279)	0.177 (2.235)	0.154 (2.358)
LDC * 1970 dummy	−0.063 (1.361)	−0.064 (1.381)	−0.060 (1.308)	−0.061 (1.327)	−0.057 (1.285)	−0.061 (1.240)	−0.056 (1.303)
LDC * 1980 dummy	−0.140 (2.251)	−0.141 (2.291)	−0.136 (2.212)	−0.135 (2.227)	−0.135 (2.214)	−0.140 (2.119)	−0.132 (2.260)
R^2	0.859	0.861	0.860	0.861	0.860	0.840	0.866
S	0.112	0.112	0.112	0.112	0.112	0.119	0.110
Sum of squared residuals	0.896	0.896	0.899	0.898	0.898	1.028	0.901

[a]Numbers in parentheses are t-ratios.

Table 10

Estimates of the degrees of local returns to scale.[a]

	Quantity of machinery per farm in horsepower (X_5)					
	0.001	0.01	0.1	1	10	100
Degree of local returns to scale (μ)	0.932	0.992	1.052	1.112	1.172	1.232

[a]The degree of local returns to scale, μ, is given by $=1.112+0.026^{*}\ln X_5$ where X_5 is the quantity of machinery per farm in horsepower.

$$\ln y_{it}=\beta_0+\sum_{j=1}^{5}\beta_j \ln X_{ijt}+\frac{1}{2}\delta_{55}(\ln X_{i5t})^2 \tag{17}$$

where we have suppressed the technical efficiency and technological change terms. This form of the production function does not have a fixed degree of returns to scale. Instead, the degree of returns to scale varies with the quantity of the machinery input.

By defining

$$\mu_i(X_i)=\left.\frac{\partial \ln F(\lambda X_i)}{\partial \ln \lambda}\right|_{\lambda=1} \tag{18}$$

as the degree of local returns to scale,[19] where $F(\cdot)$ is the production function and X_i is the vector of inputs, we obtain for the production function in eq. (17) that

$$\mu_i=\sum_{j=1}^{5}\beta_j+\delta_{55}*\ln X_{i5t}=1.112+0.026*\ln X_{i5t}. \tag{19}$$

The different estimated degrees of local returns to scale corresponding to different levels of machinery per farm are presented in table 10. (Recall from table 1 that the quantity of machinery per farm ranges between 0.001 and 127.8). Eq. (19) implies that when the quantity of machinery input per farm is low, there are slightly decreasing returns to scale; when the quantity of machinery input per farm is high, there are significant increasing returns to scale. The scale effects are therefore, as described by Hayami and Ruttan (1985), non-neutral. Incidentally, since the DC's have, on the whole, higher machinery inputs per farm than the LDC's, the average DC's are likely to

[19]For a justification of this formula, see, for example, Lau (1987).

Table 11

Comparison of the estimated production elasticities.[a]

Variable	Cobb–Douglas	Transcendental logarithmic ($X_5 = 1$)
Labor	0.325 (4.333)	0.396 (5.638)
Land	0.668 (5.793)	0.403 (3.282)
Livestock	0.134 (2.249)	0.143 (2.634)
Fertilizer	0.057 (2.173)	0.058 (2.455)
Machinery	0.061 (2.751)	0.109 (4.683)
Technical education	0.095 (3.816)	0.108 (4.714)
Returns to scale	1.245	1.109

[a]Numbers in parentheses are t-ratios.

operate in a region of increasing returns and the average LDC's are likely to operate in a region of decreasing or constant returns to scale, lending some support to the original conclusion of K-H-R.

It is instructive to compare the production elasticities estimated from the Cobb–Douglas and the transcendental logarithmic production functions (see table 11). The estimated production elasticities for all the factors other than land and machinery appear quite robust in the sense that they do not differ much between the two specifications. However, there are significant differences in the estimated production elasticities for land and machinery. Specifically, the estimated production elasticity for land is lower and the estimated production elasticity for machinery is higher in the transcendental logarithmic model.

Under competitive conditions the factor shares of the *variable inputs* in the value of gross output may be equated to the corresponding production elasticities. The factor share of the fixed input, in this case, land, is determined as a residual (one minus the sum of the production elasticities of the variable physical inputs) and is in general not necessarily equal to the production elasticity. The estimated residual factor share of land is 0.423 for the Cobb–Douglas case and 0.294 for the transcendental logarithmic case (with $X_5 = 1$). Moreover, the factor share of land for the transcendental logarithmic case will decrease with increases in machinery per farm. It will therefore tend to be higher for the LDC's (than 0.294) and lower for the DC's on average. The transcendental logarithmic results thus appear to be

Table 12

Estimates of technical progress (percent per annum).

	1960–1970	1970–1980
LDC's	0.42	−0.25
DC's	0.98	0.70

more consistent with the limited information available on the share of land rent in the value of gross output of agriculture across countries.[20]

Finally, we observe that technical education has a positive and statistically significant estimated coefficient of 0.1 which implies that a 10 percent increase in the number of agricultural graduates above the secondary level per 10,000 economically active male population in agriculture leads to a 1 percent increase in the gross agricultural output. However, care must be exercised in interpreting this coefficient as it may have represented not only technical education but also agricultural research and development and extension, and other public agricultural investments which are likely to be correlated with technical education. The estimated technological change coefficients imply the estimates of technical progress in agricultural production for the LDC's and DC's for the decades of 1960's and 1970's in table 12.[21] There is some evidence of a slight retrogression in the LDC's in the decade of the 1970's. It is conjectured that the lower estimated rates of technical progress may be due to embodiment (at least in part) of technical change in new investments and the relatively lower rate of agricultural investment in the LDC's.

7. Conclusions and extensions

What we have learned from this study? We do not claim that we have found the definitive meta-production function for world agriculture even though the transcendental logarithmic results appear quite reasonable. The precise form of the meta-production function awaits further confirmation with additional new data. However, we do find that it is important to take into account the possible existence of intercountry differences when estimat-

[20]One may argue that for LDC's labor, rather than land, is the residual claimant to the gross output. In that case the estimated share of labor is 0.080 for the Cobb–Douglas case and 0.287 for the transcendental logarithmic case, making the Cobb–Douglas case even more implausible.

[21]We take into account that the measured quantities of outputs for 1980 are averages of the years 1975–1980 rather than 1977–1982.

ing a meta-production function (or for that matter any other kind of function) with intercountry data. There is a cost in doing so, in the form of a reduction in the number of available observations. For example, by first differencing, we reduce the size of the sample by a third. This will, *other things being equal*, increase the variance of the resulting estimators. However, this must be balanced against the possibility that if the intercountry differences are truly significant, estimates that ignore such differences will be biased. In the absence of a priori knowledge to the contrary, it is better to allow for the existence of intercountry differences, even though they may in fact be negligible, to ensure that there are no significant biases at the cost of a slight loss of efficiency. After all, the estimators will remain unbiased. We also find that it is important to use a flexible functional form when estimating a meta-production function with intercountry data. There will also be a reduction in the degrees of freedom but there will also be a reduction in the possibility of bias.

The specific finding that the returns to scale are variable, depending on the quantity of machinery input per farm, is a priori plausible and consistent with the general conclusion reached by Hayami and Ruttan (1985); it is also consistent with some unpublished work of Hayami and Kawagoe (1987) using aggregate time-series data from Japan. The finding that technical education has an economically as well as statistically significant elasticity of 0.1 in agricultural production is interesting and important.

The use of country and factor-specific efficiency factors in meta-production functions can be easily extended to the case in which they are variable rather than constant over time. In fact, for the Cobb–Douglas model, if the efficiency factors are of the constant exponential form, then a second differencing of the production function will eliminate the country-specific technological change effects. In general, with a sufficiently long time-series and a flexible functional form, one can estimate country and factor-specific time-varying efficiency factors which may further depend on other environmental, institutional and policy variables simultaneously with the meta-production function. For example, the efficiency factor for land may be assumed to depend on the climate of the particular country.

Within the meta-production function framework, one can also take into account vintage effects of the machinery and the possibility of embodiment of the technological progress in new inputs. A full implementation of this approach will enable us to obtain better and more robust estimates of the meta-production function, to identify the country-specific paths of evolution of the agricultural technology (which may be further explained on the basis of country-specific environmental, institutional and policy factors), to measure the gap between a country's level of technology and the frontier of the meta-production function, and to project country-specific paths of evolution of the agricultural technology for the future.

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