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Rodolfo Cermeño y G.S. Maddala

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Rodolfo Cermeño

División de Economía (CIDE), Centro de Investigación y Docencia Económicas
Carretera México-Toluca 3655
Lomas de Santa Fé, 05100, México, D.F.
rcermeno@dis1.cide.mx

G.S. Maddala

Department of Economics
The Ohio State University
1945 North High St., Room 410
Columbus, OH 43210, USA
maddala.1@osu.edu

Abstract

This paper uses a panel data production function framework with stochastic technology trends to re-examine the inter-country agricultural production function. The focus is on the dynamics of technology and the type of (aggregate) returns to scale. The study is implemented both at the world level and by groups of countries using a panel data set on quality-adjusted agricultural inputs and outputs for 110 countries over a period of 31 years. Instead of usual deterministic time trends, a dynamic error-components model is used to model technology. This specification results in a well-defined common factor dynamic process for agricultural labor productivity. The hypothesis of non-stationary technological levels and constant returns to scale is tested by means of a LR test carried out on the Within residuals. The results support stationary technology processes and decreasing (aggregate) returns to scale. The accuracy of the error-components specification for technology is, finally, evaluated by testing its implied common factor restrictions. Some evidence in favor of this specification is found.

Key words: agricultural productivity, dynamic error-components models, LSDV estimator, unit roots, common factor restrictions, LR test.

JEL classification: C23, Q10.

Introducción

The production function framework has been widely used since the seminal work by Cobb and Douglas (1928). Over the years, interest has shifted from the macro to the micro level and panel data techniques have become dominant, because they make it possible to control for unknown individual or time effects. Nonetheless, the questioning of the empirics of production functions has been profound and numerous.[1] Two main issues were pointed out since early work: measurement and identification. Perhaps, work on the former has been somehow successful but not on the later. As Griliches and Mairesse (1995) point out, with a few exemptions, the identification problem has been largely ignored. In fact, the fundamental problem is that outputs and inputs are chosen simultaneously by producers in some optimal way, and therefore a regression approach were inputs are treated as fixed may not be appropriate.

Another important question is related to functional forms. Unfortunately, economic theory is not at all informative in this respect. More important, technological levels, and technological progress are not observable and therefore they have to be modeled implicitly or explicitly. At least three approaches have been pursued in this respect. One of them is the "Solow residuals" approach, which measures growth of technology as output growth not accounted for by input growth. When applied to cross-sectional data this approach intends to capture the technological level through an intercept term in the production function and, if data on the same units at some other point in time is available, technological growth is inferred by looking at the difference in intercepts. Another approach has been to model technology as an exponentially growing process, which resulted in a linear time trend included in the log linear transformation of the production function. In both cases, technology grows deterministically at some constant rate, which is not very informative. A more interesting approach has been to proxy the technological level by a set of variables, such as education and R&D expenditures, and to include them in the production function equation as "non-traditional inputs". This approach has proven to be successful as the impact of such variables on output growth has been reported significant. Obviously, this approach assumes that the included "non-traditional inputs" are good proxies of the unknown technological process for, otherwise, this procedure may produce biased results.

This paper uses a panel data production function framework to study agricultural labor productivity at the world level and by groups of countries, the main focus being the identification of the dynamics of the technological process and the type of (aggregate) returns to scale. Instead of modeling technology trends in a

[1] See Griliches and Mairesse (1995) for an excellent discussion of a number of issues in this area of research.

deterministic way, an explicit dynamic stochastic process is proposed. Specifically, a dynamic error-components model is used here to represent the, unknown, level of technology underlying the relationship between output and traditional inputs. Justification for adopting such an approach is mainly on empirical grounds. Availability of 31 years of information makes the focusing on dynamics a feasible task. To put it differently, inclusion of non-traditional factors would be only at the (high) cost of reducing the time dimension of the panel to just 6 observations, as information on those variables is only available on a quinqennial basis. And, since the cross-sectional dimensions of the panels are not as large as usual micro panels the entire estimation enterprise may happen to be unreliable.

Modeling technology trends as a panel data dynamic process would be informative on the overall importance of factors other than traditional inputs, even though they are not observed (they are not available in this case). Thus the proposed approach is not in conflict with those emphasizing the role of education and R&D expenditures as it focuses on tracing out the dynamics of all those factors taken together. Interestingly, the one-way dynamic error components model results in a well defined AR(1) process for per-capita output which includes current and lagged per-capita inputs as regressors. This specification resembles, in some way, the well-known Balestra-Nerlove (1966) model.

A number of papers have focused on estimating aggregate agricultural production functions using cross-country information. A few examples are Mundlak and Hellinghausen (1982), Hayami and Ruttan (1970), Kawagoe, Hayami and Ruttan (1985), Moll (1988), Evenson and Kislev (1975), Nguyen (1979), and Trueblood (1996). Most of these studies, however, have faced the constraint of having a very limited time dimension of the sample. Consequently, focus on building up a formal dynamic framework has been limited if not absent. Technology trends have usually been modeled in a deterministic way. Also the issue of the type of returns to scale underlying aggregate agricultural production functions has been controversial and it has not always been tested formally. The approach followed here intends to exploit the time dimension of the sample, integrating the two previous issues in a single and simple framework that combines a production function with technological trends represented by a dynamic stochastic process.

Some remarks on the approach used in this paper are worth mentioning. The simultaneity and identification issues are not undertaken here because of the non-availability of cross-country data on prices of outputs and inputs. The Cobb-Douglas specification, its implied homogenous relationship between output and inputs, and the assumption of neutral technical progress may be questioned, but it does not sound unreasonable to use this framework because of its simplicity, at least as a starting point. Even though a Cobb-Douglas specification underlies the whole approach of this paper, it is not restricted to the case of constant returns to scale. In fact, both constant returns to scale as well as non-stationary technological processes will be tested for jointly. Not less important is the problem of allowing for heterogeneity only through individual effects. In fact, this can be very restrictive. However, fully allowing for heterogeneity, i.e. using a SUR approach is, unfortunately, unfeasible for the particular dimensions of the panel at hand. Instead, different sub-samples of countries are considered with the hope that the homogeneity restrictions, imposed a priori, would be less important.

The rest of the paper is organized as follows. Section 2 describes the basic econometric model. Section 3 formulates the joint-test for non-stationarity and constant returns to scale. Section 4 outlines the testing procedure for the common factor restrictions. Section 5 reports the empirical results, and Section 6 briefly concludes.

The Model

Consider the following specification of the production function:

$$Y_{it} = F(X_{it}^1,\dots,X_{it}^k,e^{v_{it}}), \tag{1}$$

where $i=1,\dots,N$ indexes the cross-sectional units and $t=1,\dots,T$ indexes the time dimension. Thus, Y_{it} represents total output of unit *i* at time *t* and $X_{it}^j,(j=1,..k)$, denotes the corresponding quantities of each of the inputs. The term $e^{v_{it}}$ represents the level of technology, which is allowed to evolve stochastically. Specifically, the term v_{it} is assumed to follow the process:

$$v_{it} = \mu_i + \phi v_{it-1} + \varepsilon_{it}, \tag{2}$$

where $\varepsilon_{it} \sim iid(0,\sigma_\varepsilon^2)$ is the error term and μ_i represent individual specific effects. It is assumed that the AR parameter, ϕ, is fixed and the terms ε_{it} and μ_i are uncorrelated. The stochastic process given by equation (2) is referred to as one-way dynamic error- components model or, simply, as dynamic panel data model, i.e. see Hsiao (1984) or Baltagi (1995). This process, however, may not be assumed to be stationary a priori. This issue will be investigated here. Since (2) is not directly observable, it is necessary to make specific assumptions on the production function $F(\dots)$ in equation (1) and look at the implications of process (2) on the dynamics of an observable variable, output per unit of labor (or labor productivity) in this case.

Specifying $F(\dots)$ as a Cobb-Douglas production function in (1), using the process given by (2), and taking labor as the *k*th input, yields the following dynamic process:

$$(1-\phi L)y_{it} = (1-\phi L)\sum_{j=1}^{k-1}\alpha_j x_{it}^j + (1-\phi L)(\sum_{j=1}^{k}\alpha_j - 1)x_{it}^k + \mu_i + \varepsilon_{it}, \tag{3}$$

where: $y_{it} = \ln(Y_{it} / X_{it}^k)$ denotes the logarithm of output per unit of labor, $x_{it}^j = \ln(X_{it}^j / X_{it}^k)$ is the logarithm of the quantity of input j per unit of labor $(j = 1,...,k-1)$, α_j is the elasticity of input j (j=1,...,k-1), $x_{it}^k = \ln X_{it}^k$ is the logarithm of the level of labor, and L is the lag operator. All other coefficients are as defined before.

The error-components specification of technology implies, then, a well defined common factor dynamic process for output per unit of labor. Current and lagged quantities of both inputs per unit of labor and levels of labor (in logarithms) are included as regressors. These are given by the first and second terms of the right hand side of equation (3). The second term appears since constant returns to scale are not assumed to hold a priori. Notice that model (3) resembles, in some way, the well-known Balestra-Nerlove (1966) model.

A joint test for non-stationary technology and constant returns to scale

This paper follows an avenue of testing which exploits the implied restrictions of the error-components representation of technology on the per-capita output process. This is a joint test for non-stationarity and constant returns to scale. Equation (3) can be written in a more familiar way as

$$\Delta y_{it} = \varphi y_{it-1} + (1-\phi L)\sum_{j=1}^{k-1}\alpha_j x_{it}^j + (1-\phi L)(\sum_{j=1}^{k}\alpha_j - 1)x_{it}^k + \mu_i + \varepsilon_{it}, \qquad (4)$$

where $\Delta y_{it} = (y_{it} - y_{it-1})$ and $\varphi = (\phi - 1)$. This will be the unrestricted model.[2] A number of lagged differences of y_{it} can be added to the right hand side of the model to account for the presence of auto correlation in practice. The joint null hypothesis of non-stationarity and constant returns to scale implies the following restrictions:

$$\varphi = 0 \qquad (5)$$

$$(\sum_{j=1}^{k}\alpha_j - 1) = 0. \qquad (6)$$

The restricted model is, then:

$$\Delta y_{it} = \sum_{j=1}^{k-1}\alpha_j \Delta x_{it}^j + \mu_i + \varepsilon_{it}. \qquad (7)$$

The validity of restrictions (5) and (6) can be tested by means of a

[2] At this stage the common factor model given by (4) is assumed to hold a priori. A test for the validity of this specification is proposed in the next section.

Likelihood ratio (LR) test as follows. (i) Estimate the unrestricted and restricted models given by equations (4) and (7) respectively after removing the individual effects by a Within transformation. (ii) Construct the Likelihood ratio based on estimated Within residuals. Model (4) will be estimated by non-linear LS after subtracting individual means. This may be called non-linear LSDV estimator.

The hypothesis of non-stationary technology can also be tested independently of the type of returns to scale in the production function. In this case, the relevant restriction is only (5) and the restricted model becomes

$$\Delta y_{it} = \sum_{j=1}^{k-1} \alpha_j \Delta x_{it}^j + (\sum_{j=1}^{k} \alpha_j - 1) \Delta x_{it}^k + \mu_i + \varepsilon_{it} \tag{8}$$

Testing the validity of the error-components specification

In the previous section the common factor dynamic specification given by model (4) was imposed a priori. That is, the error-components specification of technology trends was taken for granted. Under the assumption of stationarity, equation (4) provides a natural framework to test for the validity of its implicit common factor restrictions. Consider the model

$$\Delta y_{it} = \gamma y_{it-1} + \sum_{j=1}^{k-1} \alpha_j x_{it}^j + \sum_{j=1}^{k-1} \beta_j x_{it-1}^j + \delta_0 x_{it}^k + \delta_1 x_{it-1}^k + \mu_i + \varepsilon_{it}, \tag{9}$$

It can be shown that by imposing the restrictions:

$$\gamma \alpha_j + \beta_j = 0, \text{ for } j = 1, \ldots, k-1, \tag{10}$$

$$\gamma \delta_0 + \delta_1 = 0, \tag{11}$$

model (9) can be transformed into model (4), with δ_0 being the returns to scale coefficient expressed as $(\sum_{j=1}^{k} \alpha_j - 1)$ in equation (4). Thus, the validity of restrictions (10) and (11) can be used to judge the accuracy of the error-components specification of technology. In this context, failure to reject the common factor restrictions will be taken as evidence in favor of the error-components specification of technology. The procedure can be outlined as follows: (i) Estimate the unrestricted and restricted models given by (9) and (4) respectively after performing the Within transformation on both of them to remove individual effects. (ii) Construct a Likelihood-ratio test based on estimated Within residuals.[3] As pointed out before, model (4) will be estimated by Non-linear Least Squares after removing individual effects. Model (9), however, is linear and will be estimated using standard LSDV estimation.

[3] Maddala (1992), pp. 255-257 discusses the testing for common factor restrictions in a non-panel context.

Empirical Results

This study uses a panel data set on quality-adjusted agricultural inputs and output for 110 countries over a period of 31 years. The information consists of aggregates at the country level. The inputs are Land, Labor, Fertilizers, Livestock and Capital. A detailed explanation of the sources and definitions is given in Trueblood (1996). Together with the complete sample (WORLD), five sub-samples are also considered in this study. These are 23 OECD countries (OECD), 22 Latin American countries (LA), 35 African countries (AF), 10 centrally planned economics (EUC) and a group of 77 less developed countries (LDC). This last sample includes the LA and AF samples plus 20 more countries. A list of the countries included in each sample is provided in the Appendix.

Table I presents the testing results on non-stationary technology (NST) and constant returns to scale (CRS). A remarkable result is the strong rejection of the joint hypothesis of NST and CRS in all cases, as can be concluded from looking at corresponding *p*-values. A similar result is found when testing the single hypothesis of non-stationary technology, independently of the type of returns to scale in the production function. These results are shown in the third column of Table I.

TABLE I

LR test for non-stationary technology and constant returns to scale

Sample	LR test for NST and CRS	LR test for NST only
WORLD	316.3823	251.8788
	(0.0000)	(0.0000)
LDC	217.5627	191.0108
	(0.0000)	(0.0000)
OECD	102.3218	70.2613
	(0.0000)	(0.0000)
EUC	37.9068	33.7026
	(0.0000)	(0.0000)
AF	128.01802	125.24504
	(0.0000)	(0.0000)
LA	36.5487	35.2288
	(0.0000)	(0.0000)

The LR test statistics were computed using Within residuals. *p*-values are shown in parenthesis. After performing the Within transformation the restricted model was fitted by OLS (LSDV) and the unrestricted model was fitted using Non-linear LS (Non-linear LSDV).

Results on the LR-test of the common factor restriction are presented in Table 2. It can be seen that the common factor restriction hypothesis is rejected in the samples WORLD, LDC and LA. In the cases of the samples OECD and EUC the common factor restriction can be rejected at 5% significance level but not at 1%. In the case of the AF sample the common factor restriction can not be rejected at significance levels less than 8.5% when constant returns to scale are not imposed. When the CRS restriction is imposed, the common factor hypothesis can not be rejected even at the 39% significance level. The results provide, then, some support in favor of the error-components specification of technology, at least in the cases of OECD, EUC and AF samples.

TABLE II

LR test for the common factor restrictions

Sample	LR test 1	LR test 2
WORLD	105.7961	80.0932
	(0.0000)	(0.0000)
LDC	41.1657	51.0410
	(0.0000)	(0.0000)
OECD	19.0919	12.8093
	(0.0008)	(0.0252)
EUC	7.1979	13.8081
	(0.1258)	(0.0169)
AF	4.0616	9.6670
	(0.3977)	(0.0851)
LA	23.2128	25.3977
	(0.0001)	(0.0001)

LR test 1 is the LR test imposing CRS. LR test 2 is the LR test without imposing CRS. p-values appear in parenthesis. After performing the Within transformation the restricted model was fitted by OLS (LSDV) and the unrestricted model by Non-linear LS (Non-linear LSDV).

Table III presents the estimation results. Based on previous testing results on the validity of the common factor restriction, the unrestricted model given by equation (9) was fitted to the samples WORLD, LDC and LA, while the restricted model given by (4) was fitted to the samples OECD, EUC and AF. As pointed out before, after removing individual effects by means of a Within transformation, the unrestricted model was estimated by OLS, and the restricted model was estimated by Non-linear Least Squares. In all cases, the coefficients on lagged output, which are equal to one minus the AR coefficient (ϕ), are significantly different from zero, clearly rejecting the single hypothesis of non-stationary technological levels in all cases. These results are consistent with the ones obtained using the LR test.

Results on RTS are indicated by the coefficients on Labor. Except in the cases of AF and LA, there is evidence against the single hypothesis of constant returns in favor of decreasing returns to scale. It should be noticed, though, that returns to scale here are properly interpreted as aggregate returns to scale on traditional inputs, not as returns to scale of individual farms.

It seems worthwhile to characterize the implied process of technological progress. As expected, the individual effects are all positive and statistically significant. In order to save space, only group averages of individual effects (μ) are reported in the last row of Table III. These effects capture the influence of all factors other than traditional inputs as well as ongoing technological activity, modeled as technological level in this study. These results suggest that technological levels are, in fact, quite important even though they show a tendency to slow down over time. An interesting result is that, as one would expect, OECD and EUC countries show higher (average) technological levels than AF or LA countries. Also, OECD countries seem to have more persistent technological processes than the EUC and AF countries.

Concerning the sources of labor productivity growth (i.e. growth of per-capita agricultural output), the results suggest the following. First, the relative importance of traditional inputs (in per-capita terms) varies according to sample. For example, Land seems to be important for the AF countries, while Fertilizers and Livestock seem to have contributed significantly to labor productivity growth in the case of the EUC countries. Except for LA sample, capital (per unit of labor) also contributes significantly to labor productivity growth. The highest capital-elasticity, though, corresponds to OECD countries. Second, the stationarity of technological trends shows as a negative effect on labor productivity growth. This effect is given by the coefficient in the first row of Table III. Also, decreasing returns to scale (with respect to per-capita traditional inputs) affect negatively the rate of growth of labor productivity.

TABLE III

Estimation results

	WORLD	LDC	OECD	EUC	AF	LA
Output (-1)	-0.1849	-0.1911	-0.1825	-0.2158	-0.2472	-0.1555
	(-18.1317)	(-15.3778)	(-8.6879)	(-5.7810)	(-11.7664)	(-7.1032)
Labor	-0.9205	-0.8704	-0.8816	-0.7027	0.0419	-0.3701
	(-7.1713)	(-4.7591)	(-9.0092)	(-2.4407)	(0.3414)	(-1.2301)
Labor (-1)	0.8282	0.8225				0.4009
	(6.4244)	(4.4576)				(1.3221)
Land	0.0455	0.1549	0.0038	-0.3013	0.6108	0.2261
	(1.4347)	(2.2857)	(0.1531)	(-0.9731)	(5.8934)	(1.7978)
Land (-1)	-0.0027	-0.0583				-0.1512
	(-0.0829)	(-0.8391)				(-1.2435)
Fert.	0.0136	0.0106	0.0424	0.0665	0.0088	0.0026
	(3.2395)	(2.2400)	(2.0118)	(4.2972)	(1.5245)	(0.3687)
Fert. (-1)	0.0021	0.0018				0.0155
	(0.5100)	(0.3812)				(2.1614)
Livest.	0.03849	0.0146	0.0302	0.4822	0.1075	0.0367
	(1.9238)	(0.6344)	(0.5038)	(4.9877)	(2.6951)	(1.5076)
Livest. (-1)	-0.0240	-0.0184				0.0090
	(-1.1993)	(-0.8036)				(0.3672)
Capital	0.0737	0.0653	0.1331	0.1058	0.0849	0.0346
	(4.8696)	(3.5896)	(6.2104)	(5.6388)	(4.8110)	(1.2699)
Capital(-1)	-0.0534	-0.0440				-0.0352
	(-3.6464)	(-2.4923)				(-1.3572)
$\bar{\mu}$	1.6757	1.4812	2.3127	1.9077	1.1742	0.4516

Numbers in parenthesis are t-ratios. The coefficient on lagged output is the estimate of (ϕ-1). The coefficient on the of Labor input (log level) indicates the type of RTS. X(-1) denotes one period lag of the variable X. $\bar{\mu}$ is the group average of individual country specific effects.

Overall, the influence of per-capita traditional inputs on labor productivity growth seems to be minor when compared to the effect of all other factors captured by the individual specific effects.

Regarding inter-country comparisons on labor productivity growth, the previous results would suggest that it is not the type of (aggregate) returns to scale, decreasing returns to scale in this case, the main source of differences but the technological progress, captured through the one way error-components specification in this study. Thus, in terms of economic policy, it would help to know how effective are policies in reducing the gaps in the technological trends across countries and, perhaps, in giving more persistence to such processes.

Summary

This research has focused on studying the dynamics of agricultural labor productivity defined as per-capita agricultural output. Modeling the (unobserved) technological trends with a one-way error-components model has resulted in a well-defined AR (1) process for per-capita output in the fashion of the well-known Balestra-Nerlove (1966) model. In this setting it has become possible to test for the joint hypothesis of non-stationarity and constant returns to scale. Also, testing the validity of the common factor restriction becomes a natural way to test for the accuracy of the error-components specification of technology. The empirical results strongly reject the joint hypothesis of non-stationary technological levels and constant returns to scale, apparently in favor of stationary technological levels in all cases, and decreasing returns to scale in most cases. Some evidence supporting the error-components specification of technology is also found.

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APPENDIX

Description of Samples

LATIN AMERICA (LA) includes the following 22 countries:
Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Cuba, Dominican Republic, Ecuador, El Salvador, Guatemala, Haiti, Honduras, Jamaica, Mexico, Nicaragua, Panama, Paraguay, Peru, Trinidad and Tobago, Uruguay, Venezuela.

AFRICA (AF) includes the following 35 countries:
Algeria, Angola, Benin, Botswana, Burkina Faso, Cameroon, Central African Republic, Chad, Congo, Cote d'Ivoire, Egypt, Ethiopia, Ghana, Guinea, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritius, Morocco, Mozambique, Nigeria, Senegal, Sierra Leone, Somalia, South Africa, Sudan, Surinam, Tanzania United Rep., Tunisia, Zaire, Zambia, Zimbabwe.

CENTRALLY PLANNED (EUC) includes the following 10 countries:
Albania, Bulgaria, China (Mainland), Czechoslovakia, Hungary, North Korea, Poland, Romania, Un. Sov. Soc. Rep, Yugoslavia.

OECD includes the following 23 countries:
Australia, Austria, Belgium-Luxembourg, Canada, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States of America.

LDC includes 77 countries. In addition to AF and AL countries this sample includes the following 20 countries:
Afghanistan, Bangladesh, India, Indonesia, Iran, Iraq, Israel, Jordan, South Korea Republic of, Malaysia, Myanmar, Nepal, Pakistan, Papua New Guinea, Philippines, Saudi Arabia, Singapore, Sri Lanka, Syrian Arab republic, Thailand.

WORLD includes LDC, OECD and EUC countries.