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CRITICAL ISSUES IN BRAZIL'S ENERGY SECTOR

CONVERGENCE, REGULATORY DISTORTIONS, DEREGULATORY DYNAMICS AND GROWTH EXPERIENCES OF THE LATIN AMERICAN AND BRAZILIAN ECONOMIES

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1. Introduction

In this short monograph we provide an economic analysis of past governmental practices and potential impacts of modifications in those practices that affect the development process and international competitiveness of the Latin America and Brazil. Our research provides an empirical analysis relating the institutional constraints that exist in Brazil and Latin America with the level and future course of development. We utilize different methodologies to measure efficiency and productivity levels, as well as changes in these levels over time, in order to provide a robust set of conclusions. As is well known, growth in productivity and efficiency determine the success of the development process and thus in future changes in the demands for one of the more important engines of growth, energy.

We begin with an analysis of the aggregate performance of Brazil and other comparable Latin American economies through the 1980's, a time before the movement to integrate Latin America into local and international world trade organizations had gained the momentum that accelerated during the 1990's. We then focus on a particular and important export sector of the Brazilian economy, the agricultural sector, through the 1980's, in order to develop some perspective on how governmental policies had impacted the productivity and efficiency of such a key sector. This provides us with a benchmark for the growth experience that we then examine for the 1990's, a period during which substantial deregulatory pressure was exerted on the economies of Latin American in general and in Brazil in particular. We focus on the recent aggregate performance of several of the key sectors in Latin America and Brazil, in particular agriculture, manufacturing, and the services industries. Our findings point to a rather sterile role that Latin America and Brazil have played in world economic growth. The competing and converging roles that economics and politics play in the stability of the continent is clear. The stability and economic growth of the continent, viewed by many as a major world energy producer, does not appear to have the support of history.

2. An Aggregate Overview of Development Dynamics in Latin America

We begin our analysis with a study of economic growth in Latin America and Brazil during the period leading up to the deregulatory changes that have characterized economic reform in the 1990's.

Prior research has documented unconditional convergence among industrialized countries. Baumol (1986) finds convergence in labour productivity between 1870 and 1979 for 16 OECD countries. Dowrick and Nguyen (1989) show convergence of per capita income and TFP among 24 OECD members in the post-war period. In contrast, studies that include a wider (heterogeneous) sample of economies fail to find convergence. De Long (1988) re-examines Baumol's (1986) results using a somewhat altered and enlarged sample of countries that he believes satisfies the *ex ante* criteria of selection. His expanded sample of twenty-one, after allowing for the effect of measurement bias, no longer displays a significant tendency for productivity levels to converge. Baumol and Wolff (1988) have concluded that all countries show some convergence when excluding LDCs, but larger samples do not show convergence. Their explanation is that the performance of LDCs is varied and South American countries have failed to live up to their growth potential. Hultberg, Nadiri, and Sickles (1999), Sickles and Hultberg (2001), and Hultberg, Nadiri, and Sickles (2002) framed the convergence model somewhat differently than past researchers, utilizing dynamic stochastic production frontiers models. Their findings confirmed the convergence results of past researchers but noted substantial inter- and intra-country heterogeneity in convergence rates. The convergence hypothesis is generally accepted for developed countries, however, research that examines the convergence among developing countries has not been as extensive.

We examine a group of 18 Latin American countries. One distinctive feature of Latin American countries in general is political instability in the post-war period (Dix (1992)). Political instability has strong effects on the economic activity of a nation and of the region as a whole. Failing to prove convergence, we at least demonstrate below that when excluding the five politically most unstable and educationally backward countries, there is an equalizing process of per capita income levels in the post-war period.

Two types of statistical measures have been widely used in previous research on convergence. The first is the coefficient of variation, which focuses on the cross-sectional dispersion of per capita income levels over time (Baumol and Wolff, 1986; Dowrick and Nguyen, 1988). The second common test of convergence is to regress average growth rates over an extended time period on initial per capita output (De Long, 1988). We perform these two tests, plus an additional test that explores whether the average rate of growth of poorer countries is statistically greater than the average growth rate of relatively richer nations.

We also investigate whether convergence can be explained by differences in the rate of growth of factor inputs (i.e. faster rates of capital accumulation and/or more rapid rises in labour participation) or by an exogenous tendency to catch-up in terms of total factor productivity (TFP). To determine the sources of growth, a model of comparative economic growth is estimated for two different samples of Latin American countries (L.A.), one a subsample of the other. Political stability and levels of human capital (proxied by school-enrollment ratios) are the discriminating criteria used to create these two samples. In order to determine if convergence has also been a stable feature among these countries in the post-war period, parameter stability is tested by splitting the sample period into three sub-periods (1950-60, 1960-73 and 1973-87).

Once the systematic relationship between income levels and rates of growth is estimated by the TFP catch-up rates, and the contribution of the (relative) growth rates of factor inputs is determined, it is possible to derive per capita income growth rates adjusted for catch-up. This methodology allows for a distinction between the endogenous and exogenous factors that explain the rates of growth of these samples of countries. For some of the sample countries the observed rate of growth is significantly different from the rates adjusted for catch-up. This implies that the systematic relationship of income levels and rates of growth is an important factor in explaining the difference in growth rates among these economies.

2.1 Sample Selection

The selected sample of 18 countries includes 17 Latin American continental nations (it excludes Belize, Surinam, and two colonies: French Guyana and British Guyana), and one Caribbean country. They are: Costa Rica, Dominican Republic, El Salvador, Guatemala, Honduras, Mexico, Nicaragua, Panama, Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, and Venezuela The 13-country sample excludes four Central American countries (El Salvador, Guatemala, Honduras, and Nicaragua) and one South American nation (Bolivia). The criteria used for exclusion are political stability and levels of human capital (proxied by school-enrollment ratios). Thus, the reduced sample lacks the five countries with the greatest political instability and the lowest school-enrollment ratios. Political instability is measured by an index based on the number of revolutions per unit of time. The proxy for human capital levels comes from the World Bank Tables for Literacy ratios, primary education, and secondary education. The 13-country sample is therefore thought to be homogeneous not only in terms of income levels, but also with regards to social, economic, and political institutions.

2.2 Nonparametric Tests of Convergence

The data used in this research comes from Summers and Heston (1991), who provide constant dollars estimates (in 1985 "international prices") for relative per capita GDP levels (PGDP) and its components for the period 1950-1988. The present study is structured around the trend estimates of per capita GDP (RGDP) levels. The data may represent different stages of the business cycle for each country at the period endpoints. Such purely cyclical variations in measured income levels may distort the time trends with which this study is concerned. The estimated trends were calculated for each country by regressing the log of per capita GDP on the time trend 1950-87, spliced at 1960 and 1973. The estimated model is a piece-wise polynomial function statistically tested up to the fourth order for each country's data (see Appendix I).

2.3 Coefficient of Variation (CV)

Table 2.1 presents the dispersion of the RGDP levels in the post-war period of both the 18 and 13 L.A. samples. The most notable finding is the difference of dispersion among the two L.A. samples included in Panel A and B, respectively. While the income level of the 18 L.A. sample rose by some 83 percent between 1950 and 1987 (an annual average rate of 2.2 percent), the CV dropped from 0.49 in 1950 to only 0.42 in 1986. This slight reduction in the dispersion of RGDP levels is predominantly displayed in the period of 1960-73, but there is almost no reduction in the other two periods. This slight decrease in the CV implies a very weak tendency for income levels to converge among the 18 L.A. sample in the post-war period. On the other hand, panel B, which includes the 13 L.A. sample, presents a much greater reduction of the RGDP dispersion. Observe how the CV dropped substantially, from 0.44 in 1960 to 0.34 in 1973, and from 0.34 in 1973 to 0.28 in 1987. Thus over the entire period (1950-87) the dispersion of the data fell from 0.48 to 0.28. This sharp decline of the CV indicates a strong tendency of RGDP levels to converge in this sample of countries.

Table 2.1–Dispersion of RGDP Levels in L.A., 1950-1987

	1950	1960	1973	1987
A. 18 L.A.*				
Mean	1738.67	2078.55	2990.27	3193.33
Standard Deviation	836.85	1026.06	1215.84	1359.14
Coefficient of Variation	0.481	0.493	0.406	0.425
St. Dev. of Log	0.430	0.458	0.427	0.460
*Trend Estimates***				
Coefficient of Variation	**0.492**	**0.487**	**0.414**	**0.418**
St. Dev. of Log	**0.435**	**0.454**	**0.435**	**0.451**
B. 13 L.A. †				
Mean	1939.15	2357.15	3389.46	3782.38
Standard Deviation	902.89	1070.55	1159.25	1103.13
Coefficient of Variation	0.465	0.454	0.342	0.291
St. Dev. of Log	0.450	0.448	0.369	0.301
Trend Estimates				
Coefficient of Variation	**0.477**	**0.445**	**0.343**	**0.285**
St. Dev. of Log	**0.457**	**0.439**	**0.367**	**0.290**

Data Source: Summers and Heston (1991).
* The 18 L.A. countries are the following: Costa Rica, Dominican Republic, El Salvador, Guatemala, Honduras, Mexico, Nicaragua, Panama, Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay and Venezuela.
** Trend levels have been estimated by regressing the log of per capita GDP on time trend 1950-87 spliced at 1960 and 1973; the estimated model is a piece-wise continuos polynomial function statistically tested up to the fourth order for each country's data (see Appendix I).
† The 13 L.A. is comprised by excluding the following countries from the 18 L.A.: El Salvador, Guatemala, Honduras, Nicaragua and Bolivia.

By comparison, Baumol and Wolff (1988), using the Summers and Heston (1984) data set, showed that there is a sharp break in the behavior pattern of the sample that includes fewer than the 16 countries ranked highest in terms of per capita income levels in 1950. The coefficient of variation fell steadily from 0.2 in 1950 to 0.14 in 1980. By contrast, the patterns of the CV do not display convergence in larger samples of countries. Dowrick and Nguyen (1989) use the Summers and Heston (1988) data set and focus on the members of the OECD for the post-war period. It is interesting to observe that the reduction in dispersion between the OECD and the 13 L.A. countries is virtually the same. The dispersion of the data fell from 0.45 in 1950 to 0.27 in 1985 in the OECD countries, while the dispersion decreased from 0.48 in 1950 to 0.28 in 1987 for the 13 L.A. countries. Although the magnitude of the reduction of the CV is very similar in these two samples, it is important note that the greater decline of the CV in the OECD sample is observed in the sub-period of 1950-60 (the CV in this period represents fifty percent of the reduction observed in the whole sample period), while the CV of the 13 L.A. sample experiences its sharpest decline in the sub-period of 1960-73.

In order to test (nonparametrically) the hypothesis that the poorer countries have indeed grown faster than the richer ones, the L.A. samples were divided, based on the RGDP mean at the beginning of each period under analysis. The results of the average growth rate differentials for the poorer and richer halves for both L.A. samples are summarized in Table 2.2. Panel A contains the 18 L.A. sample results. The difference in the mean growth rates is not statistically significant, even though the RGDP grew faster in the poor countries relative to the rich countries (except for the period 1973-87). This implies that in the 18 L.A. sample the average relative growth rate differential between the poorer and the richer sub-samples was not sufficient to support a greater reduction in the dispersion of RGDP levels in this sample period. This is consistent with the results presented in Table 2.1.

Panel B presents the average growth rate differentials of the 13 L.A. sample. The results confirm that, on average, the poorer countries grew faster in each of the three sub-periods, but the difference in the mean growth rates is not statistically significant in the sub-period of 1950-60. Nevertheless, the existing gap between the average rates of growth of the relatively richer and the relatively poorer economies is significantly positive for the two subsequent sub-periods of 1960-73 and 1973-87, as well as for the whole period of 1950-87. Thus, RGDP levels in the countries which were poorer in 1960 and 1973 grew significantly faster on average (at 3.66 and 1.36 percent per year respectively) than in the richer countries (2.13 and 0.36 percent per year respectively). Consistent with this result, the countries with relative lower RGDP levels in 1950 grew significantly faster on average in the entire sample period (at 2.36 percent per year), than those with higher RGDP levels in 1950 (at 1.36 percent per year). The results obtained in this section under this nonparametric test of convergence are consistent with the disparate of income levels. The RGDP level differentials among the 13 L.A. countries indeed constitute a potential for the relatively poorer countries to experience more rapid growth than the relatively richer nations and, subsequently, to encounter a reduction in the dispersion of RGDP levels through the post-war period. Conversely, among the 18 L.A. countries the relatively poorer sub-sample was not, on average, more dynamic than the relative richer sub-sample. Consequently, this sample of countries did not experience reduction in the dispersion of RGDP levels.

Table 2.2–RGDP Growth Rates of the Richer and Poorer Halves in L.A.*

	1950-60	1960-73	1973-87	1950-87
A. 18 L.A.				
Richer Countries				
Average Growth	1.74	2.46	0.60	1.36
St. Dev.	0.78	1.28	0.90	0.58
Poorer Countries				
Average Growth	1.82	3.35	0.44	1.79
St. Dev.	1.78	1.30	1.79	1.02
B. 13 L.A.				
Richer Countries				
Average Growth	**1.74**	**2.13**	**0.36**	**1.36**
St. Dev.	0.78	1.40	0.70	0.58
Poorer Countries				
Average Growth	**2.35**	**3.66**	**1.36**	**2.36**
St. Dev.	1.60	1.30	0.90	0.81
T-Statistic	*0.90*	*1.95*	*2.13*	*2.58*

Data Source: as for Table 2.1

Notes: *The growth rates comes from the slope of the trend estimated by regressing the log of per capita GDP on time trend 1950-87, spliced at 1960 and 1973; the estimated model is a piece-wise continuos polynomial function statistically tested up to the fourth order for each country's data (see Appendix I). The rich and the poor halves are divided by the average RGDP level of the first year of each period. The richer halve of the reduced sample is comprised by the same five countries from 1950 to 1973: Argentina, Chile, Mexico, Uruguay and Venezuela. From 1973 to 1987, Chile is replaced by Brazil. The t-statistic tests the null hypothesis that the average growth rates of the two sub-samples are the same. The critical value of this statistic at the five percent level of significance, with 8 degrees of freedom, is 1.85.

It is important to emphasize that the differences in the results obtained between the 18 L.A. and 13 L.A. samples are explained primarily by the exclusion of four Central American countries and one from South America which are considered the most politically unstable nations with the lowest accumulation of human capital from the 18 L.A. sample[1]. In the last 20 years, these economies have continuously suffered political crises that have had a deleterious impact on international investment and the existent capital stock. Political volatility and social crises are equivalent to a decline in the security of individual property rights, creating an uncertainty about

[1] The revolutions and coups indexes, and primary and secondary-school enrollment ratios, as proxy for human capital, are included in the Appendix II and III. The countries excluded are: El Salvador, Guatemala, Honduras, Nicaragua from Central America and Bolivia from South America.

whether people can realize the benefits of investment in physical and human capital. This increased uncertainty will tend to lower investment and growth. Similarly, with an increase in tax rates or other governmental distortions, the aggravation of property rights tends to lower the steady-state of output per worker and consequently reduces the rate of growth of the state variables (see Appendix II).

Unfortunately, the statistical measures used above to test for convergence do not provide us with an opportunity to speculate about the reasons explaining the fact that connections between income levels and growth rates appear to be strong in some periods and weak in others. However, in the 13 L.A sample, it is possible to clearly see the influence of the potential for catching up. We believe that the declining variance measures should be interpreted to mean that initial productivity gaps did indeed constitute a potential for fast growth that had its effect later if not sooner. The effect of this potential became apparent to a very limited degree in the first decade. But if a country was incapable of exploiting that opportunity promptly, the technological growth potential become stronger in the subsequent periods.

2.4. The Regression Model

Following a methodological organization similar to that of Dowrick and Nguyen (1989), a simple model of comparative growth has been used. A brief description of the variables included in the model is the following: Labor productivity (Y) is the ratio of aggregate output (Q) to employment (L); output is a function of employment (L), capital stock (K), and growth in total factor productivity. These variables were denoted as X_{it}, where $X = Y$, Q, L, K for a country i (i =1,n) in year t (t =0, T). The following definitions will be used to construct the model. The level of the variable X relative to the reference country (i =1) is

$$X_{it}^{*} = X_{it} / X_{1t} ,$$

the annual growth rate is

$$x_{it} = ln\, X_{it} - ln\, X_{i,t-1} ,$$

the differential growth rate relative to the reference country is

$$x^*_{it} = ln\, X^*_{it} - ln\, X^*_{i,t-1}$$
$$= x_{it} - x_{1t},$$

and the average annual growth rate over the sample period is

$$\bar{x} = \frac{1}{T}\left(ln\, X_{iT} - ln\, X_{i0}\right).$$

The following assumptions are made about the growth process.

A3.1. Employment and the capital stock grow at a constant annual rate in each country, i.e.,

$$x_{it} = x_i \quad \forall t, \quad x = l, k.$$

A3.2. The production function is Cobb-Douglas augmented by a common rate, γ, of exogenous technological growth and a TFP catch-up function F_{it}. If the reference country is the technological leader, then γ is the rate of growth in TFP in this leading country, while the growth in F represents an additional source of growth in TFP in other countries, i.e.,

$$ln\, Q_{it} = A_i + \alpha\, ln\, K_{it} + \beta\, ln\, L_{it} + \gamma t + \lambda\, ln\, F_{it} \qquad (2.1)$$
$$0 \le \lambda \le 1.$$

A3.3. The annual rate of growth of the catch-up function is inversely related to the level of labor productivity relative to a reference country, i.e.,

$$\frac{F_{it}}{F_{i,t-1}} = \frac{1}{Y^*_{i,t-1}} \qquad (2.2)$$

Taking the first difference of (2.1) and substituting (2.2) yields the result that the growth rate of aggregate output depends on the relative level of productivity, i.e.,

$$q_{it} = \gamma + \alpha k_{it} + \beta l_{it} - \lambda\, ln\, Y^*_{i,t-1}. \qquad (2.3)$$

Assumption A3.1 allows us to derive the following equation for the differential rate of growth in aggregate output, relative to the reference country

$$\begin{aligned} q_{it}^{*} &= q_{it} - q_{1t} \\ &= \alpha k_i^{*} + \beta l_i^{*} - \lambda \ln Y_{i,t-1}^{*}. \end{aligned} \tag{2.4}$$

This equation can be expressed in terms of the differential growth rate of output per unit of labor:

$$y_{i,t}^{*} = \alpha k_i^{*} + (\beta - 1) l_i^{*} - \lambda \ln Y_{i,t-1}^{*},$$

or

$$y_{it}^{*} = \ln Y_{it}^{*} - \ln Y_{i,t-1}^{*};$$

and thus,

$$\ln Y_{i,t}^{*} = \alpha k_i^{*} + (\beta - 1) l_i^{*} + (1 - \lambda) \ln Y_{i,t-1}^{*}.$$

Solving this difference equation yields the following expression for the level of relative per capita labor productivity in the final year T:

$$\ln Y_{i,T}^{*} = \frac{[1 - (1 - \lambda)^T]}{\lambda} \times (\alpha k_i^{*} + (\beta - 1) l_i^{*}) + (1 - \lambda)^T \ln Y_{i,0}^{*} \tag{2.5}$$

In order to obtain an expression of the average annual growth rate of aggregate GDP, we have used the following additional definitions. The average annual growth rate of output per unit of labor relative to the reference country over the sample period is defined as

$$\bar{y}_i^{*} = \left[\ln Y_{i,T}^{*} - \ln Y_{i,0}^{*}\right] / T .$$

Substituting (2.5) in this last expression, the average annual growth rate of output per unit of labor relative to the reference country can be expressed as

$$\bar{y}_i^{*} = \left[\delta\left(\alpha k_i^{*} + (\beta - 1) l_i^{*}\right) / \lambda\right] - \delta \ln Y_{i,0}^{*}, \tag{2.6}$$

where

$$\delta = \left[1 - (1 - \lambda)^T\right] / T .$$

By definition, the average rate of growth of GDP can be obtained from the following expression:

$$\bar{y}_i^* = (\bar{q}_i - \bar{l}_i) - (\bar{q}_1 - \bar{l}_1) \quad (2.7)$$

From Equation (2.3) the average rate of growth of GDP for country 1 is

$$\bar{q}_1 = \gamma + \alpha \bar{k}_1 + \beta \bar{l}_1 \quad (2.8)$$

Substituting Equations (2.6) and (2.8) into equation (2.7) yields

$$\bar{q}_i = c + \alpha \frac{\delta}{\lambda} k_i + \left[1 - \frac{\delta}{\lambda}(1-\beta)\right] l_i - \delta \ln Y_{i,0}^*, \quad (2.9)$$

where

$$\delta = [1 - (1-\lambda)^T]/T$$

$$c = \gamma + \left(1 - \frac{\delta}{\lambda}\right)(\alpha k_1 + (\beta - 1) l_1)$$

Thus, the average growth rate of GDP depends on the rate of growth of factor inputs, the common rate of exogenous technological change, and the level of output per employed worker relative to the reference country in the initial year of the sample period. It is important to note that the coefficient on initial income (δ) depends not only on the underlying catch-up parameter (λ) but also inversely on the length of the period of observation. This relation predicts that the tendency for catching-up is stronger in earlier years, when productivity levels are relatively far apart, and declines over time as the gap diminishes. This gap between leaders and laggards is the simple core of the tendency for income levels to converge. As the process of convergence goes on, the gap separating laggards from leaders becomes smaller, and rates of growth decline. The catch-up effect supporting growth is self-limiting, weakening steadily as catch-up proceeds. Note also that the coefficient on the growth of capital stock is an underestimate of a Cobb-Douglas coefficient (α), since (δ/λ) is less than unity for all T greater than 1.

For the purpose of the empirical estimation of equation (2.9), it has been necessary to make some simplifying assumptions. The Latin American annual employment data is incomplete for the period of 1950-87. Therefore, it has been necessary to use economically active population

(EAP) growth as a proxy variable for employment growth[2]. It would clearly be preferable to measure labor input by hours of work rather than by people employed or by people potentially employed; however, EAP is considered the best proxy available for this sample of countries. Also, under this same constraint regarding availability of data, the initial levels of labor productivity (Y^*_{i0}) have been proxied by per capita GDP.

Since we lack estimates of capital stock for all countries in the L.A. sample a proxy has been required for this variable as well. It is a common practice to proxy capital growth by the average annual share of investment in output (I/Q). Implicit in this practice is the assumption that capital-output ratios are constant across countries and over time. Recall that the growth rate of the capital stock can be expressed as the product of the investment ratio and the output-capital ratio, i.e.,

$$\begin{aligned} k_{i,t} &= ln\left(\frac{K_{i,t-1}+I_{i,t-1}}{K_{i,t-1}}\right) \\ &\cong \left(\frac{I}{K}\right)_{i,t-1} \\ &= \left(\frac{I}{Q}\right)_{i,t-1}\cdot\left(\frac{Q}{K}\right)_{i,t-1}. \end{aligned} \qquad (2.10)$$

Thus, if $(Q/K)_{i,t-1}$ is constant in t for all i, there is a one-to-one relationship between $k_{i,t}$ and $(I/Q)_{i,t-1}$, and this assumption can be expressed as

A3.4 $\bar{k}_i = \left(\frac{\bar{I}}{\bar{Q}}\right)\cdot z$, where z is a constant.

Substituting Assumption A3.4 in equation (2.9) and adding a random error term allows the derivation of a simple equation for the average annual rate of growth in GDP

$$\bar{q}_i = c + \frac{\alpha\delta z}{\lambda}\left(\frac{I}{Q}\right)_i + \left[1-\frac{\delta}{\lambda}(1-\beta)\right]l_i - \delta ln Y^*_{i,0} + \varepsilon_i . \qquad (2.11)$$

[2] This data comes from Summers and Heston (1991) and CEPAL (Comisión Económica para America Latina). Estimations were done separately using these two data sets, obtaining consistent results under both.

This is the equation that will be used to estimate the (δ) which is used to identify the rate of catch-up (λ) from equation (2.6). The results will be presented and analyzed below.

2.5 Econometric Evidence of Total Factor Productivity (TFP) Catch-Up

The analysis in this section is based on an estimation of the econometric model of relative economic growth presented above. This specification provides information that makes it possible to distinguish if the GR5087 cross-country differences are explained by growth rates of factor inputs or by an exogenous relation of TFP catch-up. The estimated results of this model for both L.A. samples over the period 1950-87 are reported in Table 2.3.

Table 2.3–Regression Analysis of Relative Growth in L.A., 1950-87

	18 L.A.				**13 L.A.**			
	1	2	3	4	5	6	7	8
t=	1950	1950	1960	1950	1950	1950	1960	1950
Yt	-1.44	-0.42	-0.69	2.79	**-2.20**	**-1.06**	**-1.30**	**0.66**
	[-2.23]	[-0.93]	[-1.48]	[1.26]	**[-3.45]**	**[-3.36]**	**[-3.55]**	**[0.41]**
	{-2.11}	{-1.28}	{-1.71}	{1.85}	**{-3.19}**	**{-5.12}**	**{-5.25}**	**{0.73}**
EAP		1.22	1.01	1.44		**1.12**	**1.00**	**1.23**
		[4.28]	[3.61]	[4.63]		**[6.19]**	**[5.34]**	**[5.95]**
		{6.85}	{5.54}	{5.96}		**{16.60}**	**{16.70}**	**{11.80}**
I/Q		0.09	0.08	-0.28		**0.08**	**0.07**	**-0.11**
		[2.57]	[1.91]	[-1.11]		**[2.60]**	**[1.99]**	**[-0.65]**
		{3.34}	{3.17}	{-1.68}		**{3.28}**	**{3.24}**	**{-1.10}**
I/Q. Y50				-0.19				**-0.10**
				[-1.48]				**[-1.10]**
				{-2.13}				**{-1.63}**
R2a	0.237*	0.748**	0.672**	0.785**	0.520**	0.930**	0.910**	0.938**
Adj R2	0.189	0.695	0.602	0.719	0.475	0.905	0.874	0.907
RESET2b	0.61	0.93	0.44	1.62	0.85	4.69	3.79	3.72
RESET3	1.25	0.68	0.22	0.75	1.10	3.07	2.34	2.00
HETc	0.78	9.98	10.10	13.70	2.81	9.20	10.12	

Data Source: Summers and Heston (1991).
Notes: The dependent variable is the average trend growth rates (percent per year) of GDP (GR5087). The estimated trends were calculated by regressing the log of per capita GDP on the time trend 1950-87, spliced at 1960 and 1973; the estimated model is a piece-wise continuos polynomial function statistically tested up to the fourth order for each country's data (see Appendix I). Explanatory variables: Yt is the logarithm of RGDP level, relative to United States

as a technological leader, in year t. EAP is the rate of growth of the economically active population (percent per year). This variable was used as a proxy of employment growth. I/Q is the average ratio of gross investment to GDP (percent).
Estimation is by OLS. t-statistic are shown in square brackets [ ]. White Heteroscedasticity Consistent t-statistics are in curve brackets { }
a R2: **=overall explanatory power is significant at the 1 percent level on F-test; * = significant at 5 percent level.
b Tests of functional form: RESET test were carried out by including the square and cube of the predicted values of each regression as additional explanatory variables. F values are reported above for the test of the (joint) significance of the additional regressor(s). * = significant at 5 percent level.
c Test for heteroscedasticity: HET White (1980): is the chi-square statistic from the regression of the OLS squared residuals on a constant, the regressors from the equation estimated, their squares and their cross-products. With two, nine and thirteen degrees of freedom, the 5 percent critical values are 5.99, 16.92 and 22.36 respectively. None of the above statistics are significant at the 5 percent level.

Specification 5 (presented in Table 2.3) contains the results for regression GR5087 on Yt including the 13 L.A. countries. The estimated parameter, -2.20 (s.e.=0.0063), shows the tendency for convergence; that is, the estimated coefficient is negative and statistically significant (at the 1 percent level) in explaining the cross-country growth rate differentials. The negative relation predicted by the parameter indicates that GDP has been growing faster in the poorer countries[3]. The relative initial income levels alone explain 52 percent of the difference in cross-country growth rates. The sample range of RGDP50 (in 1985 international prices), which goes from $983 to $3784, explains a spread in GR5087 of about 2.63 percentage points.

Specification 1 (on Table 2.3) contains the results for regressing GR5087 on Yt including the full sample of 18 L.A. countries. The estimated coefficient is also negative and statistically significant, -1.44 (s.e.=0.0064), although the magnitude of the coefficient is substantially smaller (in absolute numbers) and its significance is lower compared to specification 5. This means that the negative relation between GR5087 and Yt is weaker in the sample of the 18 L.A. than in the 13 L.A., as expected. The relative initial income levels in specification 1 explains only 24 percent of the cross-country growth rate differentials. This implies that the relatively lower

[3] The relationship between GR5087 and Yt may also be shown by calculating their simple correlation coefficient (ρ). Under the null hypothesis, there exists no correlation between the two, while under the alternative hypothesis, ρ is different from zero. For the period of 1950 to 1987 the correlation coefficient of -0.73 is significant at the 1 percent level, so the null hypothesis is rejected, which indicates significant negative relation between the relative initial income levels and GR5086. This is consistent with our other results.

initial income levels in the poorer economies of the 18 L.A. have not constituted a strong potential to experience higher dynamism relative to the richer economies[4].

It has been observed that the tests for conditional convergence, as reported by previous studies, differ greatly depending on the sample of countries under analysis. Baumol (1986) looking at the 16 industrialized market economies, found that 88 percent of the variation in the growth rates of GDP per hour of work over the period 1870-1979 is explained by convergence. De Long (1988) built on Baumol's experience with a somewhat altered and enlarged sample of countries that he believed satisfied the *ex ante* criteria of selection. The results based on this sample of 22 economies no longer displayed a significant tendency for productivity levels to converge. Baumol and Wolff (1988) and Baumol, Blackman and Wolff (1989) showed that one can find a small number of countries (the wealthiest eight, possibly ten) that have exhibited a steady convergence since the last quarter of the nineteenth century. More importantly, they show that in the period 1950-1980, by putting 17 of the 72 countries into the *ex ante* upper-income category, 30 percent of the variation in the growth rates of GDP per capita is explained by convergence. Dowrick and Nguyen (1989), including the OECD countries in their analysis, also found a strong negative relation between income levels and rates of growth in the post-war period. They show that the initial level of income accounts for 59 percent of the difference in country growth rates, which also implies that there is a marked tendency for income levels to converge.

Convergence might result from differences in rates of growth of employment relative to population or from higher rates of investment in the poorer countries that tends to increase their capital-labor and output-labor ratios. If these were the sole explanation of convergence, the estimated coefficient on the initial income term of specification 1 and 5 presented in Table 2.3 should tend toward zero when employment growth and investment are included as explanatory variables. When one compares the estimated coefficient of Yt from specification 5 [-2.20 (s.e.=0.0063)] and specification 6 [-1.06 (s.e.=0.0031)], which correspond to the 13 L.A. sample, it is observed that even though the magnitude of the coefficient of specification 6 decreases by about 50 percent, it remains at the same level of significance (that is, at the 1 percent level). We

4 The lower statistical explanatory power of the relative initial income levels on the average growth rates is due to the inclusion of the 5 most politically unstable nations with the lowest literacy ratios. As was previously mentioned,

also notice that in specification 6, both the coefficients of factor inputs are significant. In contrast, comparing the estimated coefficient of Yt from specification 1 [-1.43 (s.e.=0.0064)] and specification 2 [-0.42 (s.e.=0045)], which correspond to the 18 L.A. sample, once the factor inputs are included in regression 2, the hypothesis that the coefficient of Yt is equal to zero cannot be rejected. In other words, the predictions of conditional convergence do not hold for the sample of the 18 L.A.

Having included capital and labor inputs (in specifications 2 and 6), the coefficient on initial income is interpreted as a measure of the rate of TFP catch-up. These results suggest that for both samples under analysis (18 and 13 L.A.), the endogenous characteristics of the economies have played an important part in the Latin American performance in the post-war period. These results indicate that the difference in GR5087 within Latin American countries is due partially to higher rates of investment and also to more rapid rises in labor participation in the poorer countries. Finally, the results indicate that in the 18 L.A. sample the rate of TFP catch-up is not significant, but in the case of the 13 L.A. sample TFP catch-up appears to be an important factor in explaining convergence of income levels.

A maintained assumption in the above analysis is that capital-output ratios are constant across countries, that is, the growth rate of capital stock in each country is directly proportional to its investment ratio. However, it is possible that a systematic relationship exists between capital intensity and income levels in the L.A. countries. If poorer countries have lower capital intensity, it would be expected that a given level of investment (as a share of the GDP), would represent a proportionally greater increment to the capital stock in the poorer countries. If this is so, capital deepening, in countries which started off at lower levels of capital intensity, could be an important factor that explains convergence.

In order to test the capital-deepening hypothesis, it is necessary to make two further simplifying assumptions. Firstly, it is assumed that the annual average growth rate of capital stock can be decomposed into the average investment ratio (I/Q) and the initial capital-output ratio ($(Q/K)_{i0}$, as a proxy for the average capital-output ratio), i.e.,

these countries do not meet the initial conditions for convergence.

$$\bar{k}_i = \left(\frac{I}{Q}\right)_i \cdot \left(\frac{Q}{K}\right)_{i0} \tag{2.12}$$

.

Secondly, it is assumed that there is a linear relationship between the initial output-capital ratios and the initial income levels (relative to the reference country), i.e.,

$$\left(\frac{Q}{K}\right)_{i0} = z + \alpha' ln Y^*_{i0} \tag{2.13}$$

Substituting (2.12) and (2.13) into equation (2.9) yields

$$\bar{q}_i = c + a(I/Q)_i + bl_i - \delta ln Y^*_{i0} + d\left[\left(\frac{I}{Q}\right)_i \cdot ln Y^*_{i0}\right] + \varepsilon_i \tag{2.14}$$

$$d = (\delta\alpha\alpha')/\lambda .$$

This new equation allows us to test if there is indeed an interaction between investment and initial income. If the estimated coefficient d were significantly different from zero, it could be inferred that capital-output ratios do vary systematically with income levels. Observe specification 8 in Table 2.3, where the coefficient d is insignificant on the t-test. So the hypothesis of systematic relation of capital-output ratio and income levels is rejected. This demonstrates that convergence cannot be explained by capital deepening.

There has been widespread discussion in the growth literature trying to determine if the tendency for income levels to converge can be attributed solely (or at least predominantly) to post-war reconstruction. Possibly the apparent convergence over the whole post-war period might simply be the result of the rapid growth of the economies that start with low income and low capital-labor ratios enabling them to grow more rapidly. Baumol and Wolff (1988), Abramovitz (1986), and Dowrick and Nguyen (1989), among other researchers, have shown that convergence of income levels among the industrialized economies appears to be stronger for the period of 1950-

75 than subsequently[5]. This research also demonstrates that the income convergence process in 13 L.A. is stronger in parts of the sample period. However, contrary to the experience of industrialized nations, the income levels in the 13 L.A. countries converge in a small degree over the sub-period 1950-60, and thereafter (for the sub-periods of 1960-73 and 1973-87) display a stronger tendency of income levels to converge. Furthermore, this research goes beyond previous studies in that it proves that the tendency for income levels to converge, within the 13 L.A. sample, is explained by TFP catch-up, in addition to differences in the rates of growth of factor supplies.

It remains to be shown whether these determinants behind convergence are stable features, or whether the explanatory power of these factors has changed during the post-war period. In order to test for parameter stability, the sample period has been divided into three sub-periods: 1950-60, 1960-73 and 1973-86. The first decade corresponds roughly to the time of intense post-war reconstruction; the second period corresponds to a period of rapid growth, and the last period represents the more recent experience of productivity slow-down and stagflation. Since each of these periods corresponds to totally different economic and political scenarios, it would be interesting to find out if the catching-up process in the L.A. countries has undergone evident changes from period to period.

The results of the pooled regressions for the three sub-periods for the 13 L.A. sample are presented in Table 2.4.

Table 2.4–Pooled Cross-Section, Over 3 Periods on 13 L.A

[5] A number of theories summarized in Barro and Sala-i-Martin (1993) suggest that the influence of imbalances between physical and human capital on growth is crucial. This imbalance is observed in countries in the aftermath of a war that destroyed primarily physical capital. A high ratio of human capital to physical capital tends to induce rapid growth in physical capital and output.

The Pooled Cross Sections Are: (i) 1950-60, (ii) 1960-73, (iii)1973-87						
	Unrestricted Coefficients			**Restricted Coefficients**		
	9 (i)	(ii)	(iii)	10 (i)	(ii)	(iii)
Yo	-0.828	-1.080	-1.420	-1.209	-1.209	-1.209
	[-1.43]	[-1.95]	[-2.24]	[-3.78]	[-3.78]	[-3.78]
EAP	1.823	1.811	0.560	1.056	1.056	1.056
	[3.81]	[5.12]	[2.31]	[6.82]	[6.82]	[6.82]
I/Q	0.066	0.065	0.076	0.084	0.084	0.084
	[1.52]	[1.35]	[1.47]	[3.33]	[3.33]	[3.33]
Constant	-0.012	-0.015	-0.018	-0.006	-0.002	-0.029
	[-1.13]	[-1.38]	[-1.47]	[-0.95]	[-0.31]	[-4.61]
Wald Test*						
Chi Sq.(6)=8.116 Prob.=0.2297						

Data Source: Summers and Heston (1991).
Notes: The dependent variable is the average trend growth rates (percent per year) of GDP (GR5060, GR6073 and GR7387). The estimated trends were calculated by regressing the log of per capita GDP on the time trend 1950-87, spliced at 1960 and 1973; the estimated model is a piece-wise continuos polynomial function statistically tested up to the fourth order for each country's data (see Appendix I). The independent variables Yo, EAP and I/Q are the logarithm of RGDP level, relative to United States as a technological leader, in the initial year of each sub-sample period, the average rate of growth of economically active population and the average of investment/GDP ratio respectively.
* Wald Test for parameter restrictions.

The parameters have been estimated by Seemingly Unrelated Regression (SURE). Observe that the coefficient of TFP, on estimation 9(i), which corresponds to the 1950-60 period, exhibits a negative but statistically weak explanatory power on cross-country growth rates. On the other hand, note that the estimated coefficients of TFP on estimations 9(ii) and 9(iii), corresponding to the subsequent sub-periods, are negative and statistically significant (at the 5 percent and 1 percent level respectively). These results indicate that TFP appears to be an important factor in explaining income convergence mainly between 1973 and 1987, after having a fragile negative association with the growth rates in the first sub-period.

Nevertheless, in specification 10 (Table 2.4), observe that by imposing linear restrictions in the parameters (assumed to be equal for the three sub-periods), the hypothesis that all slope coefficients are equal across the three sub-periods cannot be rejected (TFP catch-up is significant at the 1 percent level). These estimates provide evidence that both the TFP catch-up and factor inputs are stable factors explaining the cross-country growth rate differentials among the 13 L.A. sample.

Based on a different sample period, it is interesting to observe the similarity of the estimated coefficient on TFP from specification 6 on Table 2.3, 100δ=-1.06 (s.e.=0031), and the estimated parameter of specification 10 on Table 2.4, -1.20 (s.e.=0031). In specification 6 the catch-up is measured over 36 years while in specification 10 the catch-up is measured over 10 and 13 years respectively. Equation (2.9) is used to calculate the underlying rate of catch-up λ for these time periods. From the estimated regression coefficient on TFP, which corresponds to specification 10, the underlying rate of catch-up is λ=0.011, which corresponds to a sample period of 10 and 13 years. By way of comparison, the regression coefficient from specification 6, where catch-up is measured over 37 years, yields an estimate of the annual rate of catch-up of 0.013. From these results it can be inferred that each year a relatively poorer country tends to catch-up approximately 1.2 percentage points of the gap in TFP between itself and a relatively richer country.

This result leads to the conclusion that the processes determining 13 L.A. relative growth rates in total factor productivity have been fairly stable throughout the period 1950 to 1987. The income convergence among the 13 L.A. countries appears to be the result of the stable influence of TFP growth rates throughout the sample period. Also, it seems that the variation in factor inputs has had a permanent and important effect on the income convergence among the L.A. countries. Therefore, convergence is explained by a systematic and stable tendency for catching-up in TFP and by the variation in factor inputs.

Researchers who do not distinguish between income convergence and TFP catch-up, like Baumol and Wolff (1988) among others, have shown that convergence of income levels among the industrialized economies appears to be strong for the period of 1950-75, but insignificant subsequently. Conversely, Dowrick and Nguyen (1989), who tested for TFP catch-up among the OECD countries, after correcting for the cyclical bias, found that convergence is explained by a systematic tendency to catch-up in TFP. Moreover, they show that TFP does not present any statistically significant decline over the entire post-war period.

This research also demonstrates that the process determining relative growth rates of TFP catch-up among the 13 L.A. has been reasonably stable as an explanation of the average differentials in growth rates throughout the post-war period. This is consistent with the OECD evidence. Furthermore, the tendency of income levels to converge among the 13 L.A. economies is also explained by faster rates of capital accumulation and by more rapid rises in labor participation. Thus, the endogenous characteristics of this sample of countries have been an important factor in explaining the tendency of income levels to converge. From this, it can be inferred that higher investment ratios and superior employment growth relative to population have been fundamental factors behind the most successful economies among the 13 L.A. in the post-war period.

2.6 Macroeconomic Determinants of Growth in 13 Latin American Countries

We next test some macroeconomic hypotheses that are considered to be interesting, important or controversial, and to provide an empirical understanding of the factors behind the diverse growth experience of the Latin American economies. However, this analysis is not intended to provide a complete account of the theoretical structure of the hypotheses, but merely to give a brief exposition regarding their testable implications with respect to economic growth. The econometric results reported below cannot be interpreted as structural estimates of a well-defined model. Rather, this research investigates empirical regularities in the data, placing emphasis on some macroeconomic variables that are considered of prime interest in the economic experience of Latin America in the post-war period.

A wide body of literature uses cross-country regressions to search for empirical linkages between long-run average growth rates and a variety of economic policy, political and institutional factors. Existing empirical research has tended towards specialized topics in attempting to establish a statistically significant relationship between growth and a particular variable of interest. In this type of empirical study, it is common for authors to examine the relationship between measures of specific policy and growth in order to test some macroeconomic hypotheses while ignoring the potential importance of other variables. For example, much of the empirical literature on economic growth focuses on accounting for economic growth by measuring factor inputs. Denison (1962, 1979), Abramovitz (1986) and more recently Dowrick and Nguyen (1989) et al account for economic growth through the growth of labor and capital inputs. Other researchers such as Landau (1983), Ram (1986) and Grier and Tullock (1989) organize their empirical work using an augmented neoclassical production function to study the effect of fiscal policy on growth. Barth, Keleher, and Russek (1987) provide an exhaustive survey of these studies. Feder (1983), Edwards (1989), and Barro (1990, 1991) study the impact of trade policy on growth ignoring the fiscal indicators. Kormendi and Meguire (1985), Romer (1990a,b), and Levine and Renelt (1992) explore the impact of both fiscal and trade policy.

The previous sections of this research focused on accounting for economic growth by measuring factor inputs and TFP catch-up among 18 and 13 Latin American countries over the period 1950-87. A simple model of relative economic growth, based on neoclassical assumptions, was estimated to test if convergence can be explained by differences in the rate of growth of factor intensities and/or by an exogenous relation of TFP catch-up. This study finds that the relative rates of growth of GDP are partially explained by the relative growth rates in factor intensities, and most importantly concludes that the initial productivity gaps between leaders and laggards did indeed constitute a potentiality for fast growth. Although the nature of the research presented in previous sections provides some understanding of the detailed structure of economic growth, it remains to be investigated whether the process of TFP catch-up is due to other factors, such as the public goods nature of investment and technological development, governmental expenditures, or levels of education.

It is a common feature among cross-country growth regressions that the explanatory variables are entered independently and linearly[6]. Empirical research has also led to the specification of a linear relationship between the macro variables of interest with the average GDP growth rates. This analysis focuses on the 13 L.A. countries. Due to constraints on availability, the data covers the period 1960-87. The data comes from Summers and Heston (1991), Barro (1991), and Levine and Renelt (1992).

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[6] Kormendi and Meguiere (1985), Barro (1991), and Levine and Renelt (1992) are good examples of this methodology.

Table 2.5 anticipates this section's findings. It shows that countries with higher average growth rates of RGDP over 1960-87 (RGDP6087) tend to have a significantly higher investment share of GDP (I/Q) and larger secondary-school enrollment rates in 1960 (SEC60), than slower-growing countries. These variables present the correct sign based on the theoretical predictions, i.e. they are positively correlated with growth, except secondary-school enrollment rates. Contrary to some theories, school-enrollment rates (and literacy used to proxy human capital) are negative correlated with growth. Nevertheless, these results are consistent under the assumption of diminishing returns to reproducible factors. The simple correlation of the other variables such as inflation (PI) and standard deviation of inflation (STPI), although not significant, present negative correlation with the average growth rate of GDP per capita. Conversely, exports (X) presents a positive, but not significant simple correlation with RGDP6087. Importantly, however, none of the variables is significantly correlated with the residual from the regression of average growth rate of RGDP on the initial per capita income levels (RES), investment share of GDP, and economically active population

Table 2.5–Comparison of Cross-Country Averages in 13 L.A., 1960-87

Variable	Fast-growers	Slow-growers	t
RGDP6087	2.56	1.11	4.74*
I/Q	18.35	14.67	1.84*
SEC60	0.14	0.25	-2.47*
PRIM60	0.90	1.00	-1.67
LIT	0.69	0.77	-1.21
GOV	10.98	11.74	-0.61
X	19.86	17.71	0.49
BMP	19.85	51.18	-1.44
PI	30.78	127.49	-1.78
STPI	44.96	339.03	-1.67
REV	0.11	0.27	-1.17

Data Sources: Appendix IV contains the sources and definitions.
Notes: 13 L.A average RGDP6087=2.0. Fast-growers are the countries with higher average growth rates than the 13 L.A. average; slow-growers are countries with lower average growth rate than the 13 L.A. average. The fast-growers economies are the following: Costa Rica, Dominican Rep. Mexico, Panama, Brazil, Colombia, Ecuador and Paraguay. The slow-growers economies are the following: Argentina, Chile, Peru Uruguay and Venezuela.
The t-statistic test the null hypothesis that the average values of the two sub-samples are the same. * The null hypothesis is rejected at the 5 percent level of significance.

The empirical results presented in Table 2.6 display intuitively appealing results for a variety of macroeconomic variables to explain growth. Specification 1 (also included in Table 2.3) is considered as the base regression in this analysis[7]. One of the main objectives of this research is to find out if there are some macroeconomic indicators which are significantly related to the GDP average growth rates (GR6087), in addition to the variables analyzed in the previous sections of this research (i.e. the rates of growth of factor inputs and the initial per capita income levels)

[7] Levine and Renelt (1992) also include secondary-school enrollment rate in what they call the "base regression" or the set of "variables always included", to conduct a sensitivity analysis of cross-country growth regressions. Of the 41 growth studies surveyed, 33 include the investment share, 29 include population growth (which is used as proxy variable for employment growth) and 18 include a measure of initial income.

Table 2.6–Cross-Country Growth Regressions in 13 L.A., 1960-87

	Regressions								
	1	2	3	4	5	6	7	8	9
Constant	-0.014	-0.017	-0.025*	-0.027*	-0.025	-0.039*	-0.066*	-0.037	-0.027*
	[-1.95]	[-1.91]	[-3.17]	[-2.44]	[-2.02]	[-3.11]	[-2.47]	[-1.53]	[-2.55]
RGDP60	-1.301*	-1.32*	-1.390*	-1.410*	-1.350*	-1.071*	-1.811*	-1.741*	-1.431*
	[-3.55]	[-3.47]	[-4.59]	[-4.24]	[-3.67]	[-4.66]	[-3.39]	[-3.63]	[-3.81]
I/Q	0.069	0.074	0.069*	0.064	0.081	0.062*	0.141*	0.058	0.062
	[1.99]	[2.02]	[2.36]	[1.80]	[1.74]	[2.11]	[2.74]	[1.23]	[1.58]
EAP	1.011*	1.050*	1.230*	1.250*	1.210*	1.421*	1.401*	1.431*	1.261*
	[5.34]	[4.99]	[6.73]	[6.06]	[5.21]	[6.50]	[4.96]	[5.34]	[5.61]
SEC60						0.031	0.055	0.033	
						[1.39]	[1.17]	[0.94]	
PRIM60							0.034	-0.002	
							[1.51]	[-0.09]	
REV							-0.011	-0.004	
							[-1.17]	[-0.44]	
GSG									0.0002
									[0.16]
GOV				0.019	-0.087		-0.187		
				[0.31]	[-0.46]		[-1.57]		
PI		0.001	0.017*	0.018*	0.024	0.019*	0.004	0.019*	0.019
		[0.66]	[2.52]	[2.37]	[1.76]	[2.87]	[1.55]	[2.14]	[2.00]
STPI			-0.005*	-0.005*	-0.007	-0.005*		-0.005	-0.005
			[-2.39]	[-2.25]	[-1.82]	[-2.72]		[-1.81]	[-1.96]
X					0.038				0.009
					[0.59]				[0.42]
R2	0.91**	0.91**	0.95**	0.95**	0.95**	0.96 **	0.96**	0.96**	0.95**
R2 Adj.	0.87	0.87	0.92	0.90	0.89	0.93	0.88	0.89	0.89
SSE	0.005	0.005	0.004	0.004	0.005	0.004	0.005	0.005	0.004

Data Sources: Appendix IV contains the sources and definitions of the variables..
Notes: The dependent variables is the average growth rate of GDP in 1960-87 (GR6087). t-statistic is shown in square brackets. * =significant at 5 percent levels. R2: ** =overall explanatory power is significant at 5 percent level.

Specifications 2 and 3 include PI and STPI. In specification 2, the parameter of PI exhibits a positive but statistically weak explanatory power on the rates of growth. However, in regression 3, including the STPI, these parameters appear significant in the growth regression. The estimated coefficient of PI is 0.017 (s.e.=0.0068), which indicates that the partial correlation between PI and growth is positive and statistically significant. This result is consistent with the Tobin-Mundell hypothesis, which predicts that a more rapid growth in anticipated PI implies a more rapid shift away from the real money balances toward real capital and hence greater economic growth. By contrast, the coefficient of the STPI is -0.005 (s.e.=0.0021), which represents a statistically significant negative relation between growth and changes in PI. Consistent with Friedman's predictions, variable inflation interferes negatively, reducing economic activity. In other words, a change of 1 percent of PI from its old path decreases the rate of growth by 0.005 percentage points.

The estimated coefficient of government consumption share of GDP (GOV), included in specifications 4, 5 and 8, shows both positive and negative relations on GR6087, leading to some ambiguity. This implies that depending on the conditioning information set (or the variables included in the regression), the variable mentioned above is imprecisely related to the rates of growth. Nevertheless, these estimates consistently present weak explanatory power with respect to growth. Specification 9 includes the growth of the share of government consumption (GSG). Consistent with the study of Barth, Keleher and Russek's (1987), once it is determined that GOV has weak explanatory power on growth, it is likely that GSG effect is similarly weak. Specifications 7 and 8 include primary-school enrollment rates in 1960 (PRIM60) and SEC60 (proxying human capital) to test if the range of variation of human capital explains a significant range of variation in the rates of growth. Indeed, specification 8 nearly replicates the one used by Kormendi and Meguire (1985). The results show that these variables are not significantly related to GDP growth rates. Moreover, PRIM60 and SEC60 show opposite signs on the estimated coefficients of specification 8. These results are inconsistent with previous studies that focus on the importance of human capital and prosperity. Barro (1991) demonstrated that the school-attainment variable turns out to be positively related to growth.

As expected, the estimated coefficient of revolutions (REV), which measures political crises, is negatively related to growth, although its statistical explanatory power appears to be weak. Specifications 7 and 8 present these estimates. Nevertheless it is important to emphasize that these estimations are based on the sample of 13 countries, which already excludes the 5 most unstable nations from the original sample comprised of 18 L.A. countries. So with the exclusion of these countries, it is consistent that the explanatory power of the estimated coefficients of REV weakens in the 13 L.A. countries.

This section presents the results of an exploratory empirical study on macroeconomics factors that may affect economic growth in a sample of 13 L.A. countries. Several interesting findings have emerged from the estimations previously presented. As suggested by the neoclassical growth theory, these results confirm that economic growth is positively related to the rate of growth of EAP (proxying labor input growth rates), and negatively related to RGDP60. Importantly, these parameters were found to be consistently significant in all the estimations presented above. These results support the convergence hypothesis, widely discussed in the previous sections of this dissertation. Also, in line with the prediction of the neoclassical theory, the investment share of GDP (proxying capital input growth rates) is positively related to income growth rates, although it is only weakly related to the rates of growth statistically.

Also, the evidence that government consumption share of GDP adversely affects economic growth was found to be weak. Moreover, the growth in the ratio of government consumption to output is positive related to the growth rates, but statistically insignificant. Contrary to the results presented in Table 2.5, the parameter for secondary-school enrollment rates exhibits a positive but statistically weak explanatory power on cross-country growth rates. Consistent with previous empirical studies, we found a negative (although statistically insignificant) association between revolutions and growth. Finally, the effects of inflation and standard deviation of inflation were also explored. Contrary to Stockman's (1981) predictions, we find no evidence of a negative effect of inflation on economic growth, but instead find evidence of a positive effect consistent with the Tobin-Mundell hypothesis. However, it is confirmed that economic growth rates are adversely affected by an increase in the standard deviation of inflation.

The results presented in Table 2.6 suggest that inflation and the standard deviation of inflation are statistically significant if both are included in the regression; otherwise, with the omission of either one, the effect of the still included variable displays a weak explanatory power on the rates of growth. This implies that there is no reliable, independent statistical relationship between these two variables and growth. Since these variables are highly and positively correlated with each other (the simple correlation coefficient is 0.97) and negatively correlated with the rates of growth, once they are included in the same regression, it is expected that the estimated parameters of these variables present opposite signs. In other words, these variables exercise an offsetting effect to each other. The apparent explanatory power displayed by these variables is due to the information provided by the countries that present the lowest correlation on inflation and standard deviation of inflation[8]. Nevertheless, given the predicted relation of these two explanatory variables on growth, this result is jointly consistent with the Tobin-Mundell hypothesis and with Friedman's (1977) predictions. This result indicates that inflation is positively related to economic activity, contrary to some empirical findings, like those in Kormendi and Meguire (1985), who find that inflation has a negative effect.

However, it is important to keep in mind that in cross-section regressions the coefficients do not represent elasticity or behavioral relationships as characterized by parameters estimated from a structural model. Consequently, cross-section regressions should be perceived as establishing patterns of correlation. This implies that the sign of an estimated coefficient is the sign of a partial correlation between the rates of growth and each regressor, with the other regressor held constant. In this case the strength of the partial correlation is determined by the t-statistic. The mechanism of these parameters is provided only by theory.

There is no consensus on the theoretical framework to guide empirical work on growth, and existing models do not completely specify the variables that should be held constant while conducting statistical inference on the relation between growth and the variables of primary interest. This has produced a diverse and some times unwieldy literature, in which few studies control for the variables analyzed by other researchers.

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[8] These countries are Bolivia, Argentina, Peru, Brazil, Chile, and Uruguay. These are the countries which have experienced the highest rates of inflation among the L.A. countries in the post-war period.

Cooley and LeRoy (1981) argued that economic theory does not generate a complete specification regarding which variables are held to be constant when statistical tests are performed on the relation between the dependent variable and the independent variables of primary interest. Thus, many candidate regressions have equal theoretical status, but the estimated coefficient on the variables of interest in these regressions may depend significantly on the conditioning set of information.

Based on the results presented on Table 2.6, it was observed that only the RGDP60 and EAP remain significant through all the exploratory regressions. This result indicates that only the initial per capita income levels and the economically active population, out of the eleven explanatory variables analyzed, have an independent statistically significant correlation with cross-country growth differentials. These findings illustrate that it is very difficult to isolate a strong empirical relationship between any particular macroeconomic policy indicator and long-run growth.

2.7 Summary of Aggregate Economic Performance in Latin America Prior to the Trade Liberalizations of the 1990's

In this overview of the emerging Latin American economies entering the 1990's, the hypothesis that per capita income and TFP levels within the 13 L.A. countries have converged in the post-war period have extensively been tested. However, for the extended sample, comprised of 18 L.A. economies, convergence of income levels has not been a significant feature. The contrasting results of these two samples of countries are primarily due to the exclusion of the five most politically unstable countries with the lowest human capital accumulation. These countries exhibit both low-income levels in the initial year of the sample period, as well as low average growth rates, which violate the predictions of conditional convergence. The inferior performance presented by these nations can be explained by the political volatility and social crises that these countries have experienced in the last 20 years, which have had a deleterious impact on international investment and on the existent capital stock.

The strongest reduction in the income level differentials as well as the most significant estimates of conditional convergence for the 13 L.A. sample appears to be in the sub-periods 1960-73 and 1973-87. Conversely, the results obtained for the sub-period 1950-60 do not seem to display a significant convergence tendency. However, a simple model of comparative economic growth, which incorporates TFP catch-up as a central feature, demonstrates that parameter stability is exhibited over the three sub-periods.

When the strength of catching-up as proportional to income gaps between countries is modeled, and a distinction between growth in factor intensities and growth in total factor productivity is made, then there is evidence that within the 13 L.A. countries there has been systematic TFP catch-up throughout the post-war period. This was not the case for the 18 L.A. sample. Also, this study determines that the rate of growth of factor input intensities are significant in explaining the cross-country growth rates of both L.A. samples. Therefore, the growth rate representing the performance of each country among the 13 L.A. sample have been determined by (1) the systematic exogenous relationships between TFP growth and income level differentials among the countries and (2) the endogenous characteristics of each country, measured by the rate of growth of input factor intensities. These results depend critically on the sample selected. A natural explanation of the differences between these results could be found in the reasons used to exclude the 5 countries of the 18 L.A. sample. It could be argued that instability and changes in political regimes in Latin America is perhaps the principal factor undermining the advantages of relative backwardness for productivity growth of laggards over leaders.

Therefore, the process determining TFP catch-up has been well established as an important phenomenon explaining the difference in growth rates within the Latin American countries. Accordingly, estimates of comparative growth rates adjusted for catching up have been presented. In a number of cases within the 13 L.A. sample, the adjusted comparison of growth rates and changes in growth rates is substantially affected by TFP. This illustrates the potential bias in any analysis of comparative economic growth for a sample of countries which contains no reference to TFP. The overarching reasons explaining systematic TFP catch-up are likely to be found in some combination of the factors to which other studies have referred: the public goods nature of the technological progress, difference in sectoral productivity, liberalization in international trade and foreign capital investment. However, we believe that the lack of well-developed human capital is the main barrier facing the developing countries in their attempts to adapt and incorporate more sophisticated technologies which would launch them into a higher pattern of convergence among the industrialized economies.

3. Brazilian Agriculture

The development of agricultural technology has been and still is crucial to the evolution of humankind. Even before the industrial revolution agricultural technology changed dramatically if not in quite such a spectacular manner as in the last century. The new means of production created opportunities for supplementing and substituting the traditional factors of production, namely, land and labor by whose application the labor requirement per unit of agricultural output has been greatly reduced, as has the area of land needed per unit of product. Economists have made an exhaustive study of the progress and economic impact of the Green Revolution that has changed many developing countries traditional agricultural sectors into modern ones. However, a number of countries have been unable to complete this transition. Farm-level variation in agronomic conditions that govern the use of modern inputs and its profitability is often cited as a reason for the diverse usage of modern inputs. Mellor and Ahmed (1988) argue that the actual use of modern inputs, keeping agronomic factors constant, is a function of the conversion of its economic potential into a farmer's effective demand, the creation of an adequate supply, and its timely delivery to farmers at geographically dispersed locations. Government agricultural policies affect both the demand side through farm-level credit and extension services as well as the supply side through investment in infrastructure and research and development. Thus substantive issues arise concerning agricultural development policy in developing countries.

Shultz (1964) described the changes in technology that helped jump-start the agricultural sector's transformation from traditional to modern regimes. According to him traditional agriculture is characterized by a long run stationary equilibrium state where farmers use only well established production methods and know their marginal costs and benefits. In this regime human capital has such a low marginal product and marginal return, that it has value principally during the periods of structural change. The rate of return to new investments in physical capital is also low with respect to the rate of time preference. In contrast, the modern sector has well-established agricultural research institutes and is characterized by short lags between the development of new methods/inputs and their adoption.

One of the main issues is to analyze the factors that determine the degree of commercialization in agriculture and the quantitative significance of such factors in the farmers' adoption decisions, in order to derive and implement a sound agricultural developmental policy. The issues that affect the farmer's adoption decisions are well documented in the literature. In order to compare the distribution of returns under alternative technological regimes, farmers need to be aware of the existence of modern technology. The presence of market imperfections can affect the incentives to adopt new methods of production. These imperfections can occur in both the output and input markets and thereby affects both the demand for inputs and the supply of outputs. Divergence in the food prices paid and that received lead many farmers to concentrate production on food crops which are typically less responsive to modern inputs than cash crops. As prices received vary from market to market, the location of the farm becomes an important factor in the decision to adopt modern inputs for cash crops. On the demand side, farm size and location affect the prices that are charged for the modern inputs. Non-price constraints such as the need for complementary inputs arising from the use of a modern input may constitute an indivisible input. The lack of rental markets for farm equipment and poor credit facilities are other drawbacks in the market infrastructure. Cash constraints are very important, for example, short time credit constraints may require that fertilizer prices be lower than when these constraints were not available. This factor also highlights the importance of other sources of income such as off-farm income and such. Other "Threshold or Leading Technologies" such as irrigation, electricity and transportation are important. Poor transportation could reduce the benefits of producing marketable crops relative to subsistence crops. The literature supports the notion that sharecropping creates a barrier to the adoption process if it leads to a greater independence of the tenant from the landowner (Bhaduri, 1973; Scandizzo, 1979) or if it increases moral hazard (Newberry, 1975). The inter-linkage of markets especially when the credit is provided by the landowner, makes the nature of the contractual arrangements an important factor in the adoption of modern technology. Ecological factors like the nature of the terrain, soil quality, crop rotation practices, quality of arable land, pasture and rainfall affect the yield obtained from different technologies and the adoption decisions.

While the main issue facing developing countries remains the analyses of factors determining the degree of commercialization in agriculture and their quantitative significance in the farmer's adoption decisions, it is the severe methodological problems that arise from missing observations and measurement error that are addressed in the first essay. Most studies raise methodological problems in both the definition of variables and the choice of models. More importantly these studies are fraught with measurement error. Inappropriate policy recommendations arise as these analyses often focus on a small subset of factors affecting the decision to adopt whereas a more comprehensive model can incorporate all these inter-linkages. Whereas a limited dependent variable model or a simultaneous equation approach is more appropriate, most studies use an OLS approach. Empirical studies often employ single equation methods to analyze the factors affecting the adoption or non-adoption of one type of technology for a specific crop, thereby ignoring the simultaneous nature of the farm decision making process when more than one crop is produced and more than one kind of input is utilized. Thus one cannot ignore the interrelated technologies and interdependent relationships that exist among production activities which in turn are affected by education, distance to the market, credit constraints, tenancy arrangements and the like.

We measure the production efficiency of farmers over time to assess levels and trends in agricultural efficiency. The development of agricultural technologies has sparked productivity and dramatically increased the diversity of both agricultural practices and yields. The latter phenomenon results from a non-uniform adoption of technology. Productivity measures assume great importance as most rural economies are populated with less efficient farms. This raises the question: Is a single strategy of modernization more appropriate than a dual strategy? A dual strategy would provide high yielding farms with yield maintaining strategies and less efficient farms with yield enhancing technologies.

We attempt to identify the magnitude of productivity variations and their sources. The questions that are addressed are: Do significant differences in efficiency levels exist among farms using the same input base in order to produce the same output mix? How vastly do levels of technical efficiency vary across farms using different input bundles? Do some input mixes appear more efficient/ inefficient than others? Does adoption of modern technology increase the output levels of these output diversified farms? To what extent does tenancy status affect productivity levels? And finally, what instruments can policy makers use to affect farm-level efficiency?

There are several measures of predictive efficiency measures. Data Envelopment Analysis (DEA) is used to construct and explore the differences in technical efficiency across farms. Following the methodology of Cornwell, Schmidt and Sickles (1990) a Stochastic Frontier Analysis (SFA) model is also employed. DEA is a nonparametric, deterministic approach rooted in linear programming whereas SFA is parametric and based on statistical regression techniques. The two methods are used to estimate and predict the technical efficiencies of the farmers.

When constructing efficiency scores one assumes a homogenous technology. In this panel several input combinations are used to produce one or both outputs. Moreover, a fair proportion of the sample consists of farmers engaged in sharecropping. Tenancy status is hypothesized to affect the nature of the underlying technology beyond the input combinations used. This issue of identifying a homogenous technology is investigated by clustering farmers based on input-usage as well as tenancy status. Given three input categories, seven separate input use regimes emerge for the production of crops and livestock. The efficiency scores are compared across the two methods and clustering processes.

The characteristics of the most efficient farmers are then examined. When homogenous technology is defined as the combination of input usage: the results reveal a very small percentage of efficient farmers for all seven input regimes. All farmers on the frontier use modern inputs in greater proportion than their less efficient counterparts. The premise that sharecroppers are more efficient is investigated by comparing the efficiency scores when we control for tenancy status viz. when we do not. Full sharecroppers are more technically efficient for livestock production than their partial sharecropping counterparts. This essay proves once again the diversity that exists in terms of technology and yields. Moreover one cannot ignore the effect that tenancy contracts impose on incentives and thereby on productivity. A dual strategy would seem appropriate under these conditions.

We also investigate the anomalous results caused by the assumption of technically efficient behavior. Statistical methods have long been used to identify and estimate inefficiencies in the performances of decision-making units. The issue is particularly important for less developed countries that possess higher proportions of inefficient units. Policy decisions affect agricultural production methods, both in terms of infrastructure as well as the nature of available technology. Earlier studies have explored the nature of farm-level productivity but have failed to include this information in the estimation of the demand systems for farm-level inputs. Inconsistent results and the frequent failure of parameter estimates to satisfy regularity conditions are a common feature of these studies. Estimation of systems of derived demand equations along with the cost function relies on the standard assumption of cost minimizing behavior. This translates into all units being technically efficient. This essay investigates whether anomalous results could possibly be an artifact of the maintained assumption of technically efficient behavior. In Essay II, the predicted efficiency scores reveal a big range of efficiencies and a very small proportion of efficient farmers. The inter-related demand systems from Essay I are re-estimated. The computed technical efficiency scores are used as additional regressors. The parameter estimates are then tested to see whether any significant differences emerge in the estimates viz. when the inefficiency scores are not included.

3.1 Brazilian Agricultural Data

The Prodemata data set follows a panel of 384 farmers in Zona da Mata, located in the region of Minas Gerais, Brazil, over a six year period extending 1979 -1984. This data set has been extensively documented in previous studies. For a detailed description of the region and the data see Busom and Nerlove (1986), Desai and Vosti (1989), Nerlove etal. (1989, 1990), Bradley (1990) and Nerlove and Weeks (1992).

Before analyzing the Prodemata data set, it would be informative to briefly describe the agricultural infrastructure that exists in Brazil. Brazil is a middle-income country with 156.5

million[9] people populating an area estimated at being 851,000,000 hectares by the National Council of Geography[10] and at 846,000,000 hectares by the Population Census. Of the 8,500,000 square kilometers of land area in Brazil, an estimated 67% is forested and a large fraction of the country is made up of hilly or mountainous terrain. Although large sections of the soils in the country are poorly suited for agriculture, Brazil has the ecological conditions for the production of a vast array of agricultural products.

The importance of agricultural production serving as an "engine of growth" in the development process is a well-known fact. Theory and empirical evidence support the notion that agriculture's share in GNP declines as a country becomes more developed as productivity improves. Table 3.1 shows Brazil's performance in the agricultural arena.

Table 3.1-Average Yearly Growth Rates of Real Output for Agriculture: 1947 - 1986

	Total	**Crops**	**Livestock**
1947-50	4.3	4.4	6.2
1951-54	4.5	3.0	9.4
1955-58	4.2	5.6	1.5
1959-62	5.8	5.7	4.9
1963-66	3.2	3.0	4.7
1967-70	4.7	5.1	2.3
1971-76	5.9	5.5	6.3
1977-81	5.0	4.8	5.1
1981-86	1.8	3.9	-0.9

Source: Baer (1989), pp. 344

Agricultural production started growing more slowly in the early 60's when the Brazilian government concentrated on the industrial sector but this changed when the economy "opened" up by the mid-80's.

9 WDR, 1995, Basic Indicators, pp. 163.
10 Schuh (1970), pp. 120.

Agricultural product markets in Brazil can be distinctly categorized into products for domestic consumption versus that for export. Historically, exported products have included soybeans, oranges, sugar, tobacco, cocoa, coffee, peanuts, and cotton. Agricultural exports grew at an average annual rate of 22% between 1965 and 1977 (in nominal terms and excluding coffee exports). Traditional domestic crops have been and remain rice, edible beans, cassava, corn, potatoes, milk and onions. All these crops (with the exception of soybeans) are present in the production array of the Prodemata farmers.

Agricultural policies in Brazil encouraged the expansion of export crops (mainly coffee, cocoa and soybeans). This led to a growth in yield for several export crops and decreases in yield for most food crops. This trend can be observed (for rice, beans, coffee and soybeans) in Table 3.2.

Table 3.2-Agricultural Productivity in Brazil, Selected crops: 1947 -85

	47-49	61-63	64-66	68-70	72-74	74-76	78-80	83-85
Rice	1552	1634	1536	1464	1533	1461	1415	1700
Beans	685	659	656	634	593	566	472	454
Coffee	411	415	771	811	1192	1009	1046	1356
Soybeans	--	1056	1088	1072	1463	1660	1398	1747

Source: Baer (1989), pp. 351, Table 14.3. All figures measured in kilograms/ hectare.

With this focus on exports, there was also a shift in production methods with more traditional methods of agriculture being substituted for modern technology. Most of this change in production technologies occurred on farms concentrating on export-oriented products. This phenomena in the export sector was coupled with an ongoing shortage of domestic food crops. The Prodemata data represents this diversity of production technologies. The data set also represents the large concentration of agricultural land in Brazil which has not changed much between 1950-85. Table 3.3 depicts the prevalent inequality in land holdings.

Table 3.3-Size Distribution of Total Area: 1950-85 (Percentage Distribution)

Size (Ha)	1950	1960	1970	1975	1985
Less than 10	1.3	3.4	3.1	2.8	2.7
10-100	15.3	19	20.4	18.6	18.5
100-1000	32.5	34.4	37	35.8	35.1
1000-10,000	31.5	28.6	27.2	27.7	28.8
above 10,000	19.4	15.6	12.3	15.1	14.9

Source: Baer(1989), Table 14.5 pp. 354

Large farms have a disproportionately large percentage of the total area farmed. This picture becomes more pronounced if one looks at Table 3.4 which shows the percentage distribution of the number of establishments by size distribution. The percentage of small farms or *minifundios*, have steadily increased from 1950-85 while there has been a decline in the number of large farms or *latifundios*.

Table 3.4-Size Distribution of Number of Establishments: 1950-85 (Percentage Distribution)

Size (Ha)	1950	1960	1970	1975	1985
Less than 10	34	44.7	51.2	52.1	52.9
10-100	50.9	44.6	39.3	38	39.1
100-1000	12.9	9.4	8.4	8.9	8.9
1000-10,000	1.5	0.9	0.7	0.8	0.8
above 10,000	0.7	0.4	0.4	0.2	0.3

Source: Baer (1989), Table 14.5 pp. 354

Thus the importance of the small farmer cannot be underestimated in studying the Brazilian agricultural sector. The Prodemata data set is biased towards small farms which make up the majority of the agrarian units in Brazil. The Prodemata data set is representative of the Brazilian agricultural sector, displaying a diversity of production technologies, farm sizes and tenurial situations.

Prodemata Panel Description

The Prodemata data set has farmer level information for 384 farmers in the region of Zona da Mata. Zona da Mata is located in the south-east region of Brazil in the state of Minas Gerais. In 1985, the Southeast region of Brazil constituted 20% of the total acreage, possessed 20% of the rural workers and contributed 38% of the total value of the agricultural production in Brazil.

A baseline survey of landowners was conducted in the Zona Da Mata region of Minas Gerais before the Prodemata Project was launched to assess the situation of the farmers in the region and to identify the target population. Prodemata was an integrated rural development program implemented in Zona da Mata, over the period 1976-1984. The purpose of the project was to increase the amount of potentially arable land under plow, increase the yield on all croplands, and to improve the health and educational services available to farmers and their families. The initial survey was administered to approximately 800 farmers and was divided into 2 parts. The first part dealt specifically with agricultural output, broadly defined to include all farm products including livestock and related inputs used and outputs produced. The second part of the survey dealt with information pertaining to socioeconomic infrastructure, including education, access to credit and technical assistance, household demographic characteristics, participation in cooperatives and so on. Annual retrospective surveys continued after the Prodemata program was begun to monitor the progress of the participating farmers, especially with regard to those farmers included in the sample who did not directly benefit from the development program.

The Prodemata panel of farmers was drawn by taking stratified random samples from 12 municipalities or Municipio's. The initial panel constituted of 800 farmers but by the end of 1984, only 384 farmers remained in the sample. This attrition was primarily caused by the occurrence of land sales and migration.

The Prodemata data set has detailed panel and cross-sectional information, but like most other data possesses certain drawbacks[11]. The most important limitations are the missing observations

[11] A more detailed discussion of the data discussed in this section can be found in Nerlove (1986), Bradley (1990), and Nerlove et al. (1989,1990).

that arise from the non-use of inputs or the non-production of outputs and the missing price information that occurs if the input or output is not consumed or produced. This results in a censored sample with a truncated price vector. Additionally, there is no information on soil quality and seasonal variables side. The lack of seasonal variables limits a joint analysis of livestock-crop interactions and forces use of a separable production function for crop and livestock. Moreover there is no information on the consumption side of the farmer's decision making process while land usage variables are subject to a great deal of measurement error.

Some ecological background is important in understanding the panel as the data set does not contain soil or land quality data. Zona da Mata has a climate favorable to agricultural production with the summer season extending from May to September and the monsoon season extending from October to April. Zona da Mata has the characteristic mountains, valleys and diverse soils of the region. There are two main types of soil, namely, Latossolos which is mainly formed of clay and requires to be rotated frequently to maintain its low fertility and Podzolicos which has the elements of calcium and magnesium mixed in with the clay to make it the more fertile soil. The combination of the diverse terrain soil quality causes the water supply to be very diverse despite the presence of four rivers. The riverbeds which suffer none of the constant erosion that takes place at higher altitudes are most often used on a rotational basis for pasture and rice cultivation. The ecological characteristics of Zona da Mata follows the general characteristics of Minas Gerais which is not well endowed with soils.

In Zona Da Mata, there are nine major crops and five distinct kinds of livestock but the farmer's production array consists of only maybe three crops and maybe two to three categories of livestock. Nerlove et al. (1989) created an index of crop and livestock output by aggregating the different products according to a system of constant relative price weights. This method was executed to form two composite output categories: crops and livestock for each year. The same method of indexation was used to create three broad input categories: modern, labor and traditional inputs. These input categories were then further narrowed to construct the amount of each input applied towards a particular output to form six input categories for each of the six years. The price of corn was chosen as the numeraire as it was the most common product each year and the market for corn was well integrated across the survey period. If both price and quantity information was missing for a given farmer and a given category then the observation was set to missing. If the quantity information was present but the price information was not recorded then the Municipio average price was used. We use the aggregate crop and livestock production categories along with the indexed categories of labor, traditional and modern inputs applied towards them as output and input measures.

For livestock, the quantity produced is defined as the sum of the quantities sold and consumed. The five types of livestock used to create the aggregate index are: cattle, pigs, fowl, horses and goats. The total output of crops is measured in terms of annual gross production. The crops used towards the construction of the aggregate index are: corn, coffee, rice, tobacco, sugar, manioc, beans, sharecropped beans, tomatoes, citrus, fruits, other annuals, potatoes, horticulture and bananas.

Labor inputs are stratified as family or hired labor units applied towards the production of crops and livestock. A lack of either of these labor categories is interpreted as being the application of "self" labor only. Labor inputs to livestock comprise labor inputs to pasture and forage for cattle and specific labor inputs for pigs, fowl, horses and goats. Labor inputs to crops simply constitute labor units applied towards crop cultivation and related activities. Traditional inputs are specifically animal traction for livestock production and organic fertilizers and seeds used to raise crops. Modern inputs are most often used on a small subset of the production process. Modern inputs to crops are mechanical traction, chemical fertilizers, pesticides and hybrid seeds while those applied to livestock are veterinary expenses, modern feeds and expenditures on modern inputs used in the preparation of forage and pasture.

The crop categories used to create the labor indices were: corn, coffee, rice, tobacco, sugar, manioc, beans, sharecropped beans, tomatoes, citrus, fruits, other annuals, potatoes, horticulture and bananas. When creating the labor input group for livestock five types of livestock were used in the construction: fowl, pigs, horses, goats and cattle. Traditional and modern input indices to crop and livestock were created using the same livestock and crop categories as listed above.

Land use variables include total area owned by the farmer (AFARM), area of land under cultivation (ACROP), the area of land under pasture (APAST) and the area of land sharecropped (ASHARE) on another's farm. There is also a separate dummy variable that is created to indicate sharecropper status. This variable (KSHARE1) equals one only if the farmer is a total sharecropper which translates to him being a landless peasant. This situation arises when the area sharecropped is greater than the area owned.

Infrastructural variables present in the data set include total income earned by a farmer working off-farm in the agricultural and non-agricultural sector (stratified by man, woman and child). Household information for off-farm labor is fairly detailed. The information is stratified for each family by male, female and child and is available for both off-farm work in the agricultural and the non-agricultural sectors. A variable (TIOFJ) is created which is the value of total income earned by a family by working off farm. This is arrived at by summing over income derived from both the agricultural and non-agricultural sectors. Additional information include dummies for membership in a co-operative, credit and access to electricity. The total credit received by a farmer is further differentiated into credit received for working capital and that used for investment capital, used towards the production of crops and livestock. Due to missing data at the crop specific level, we focus only on the total credit received. The grand total for working and investment capital is obtained by summing over the credit received in either category for the following crops: bananas, beans, coffee, citrus, corn, other fruits, onion, potatoes, rice, sugar, tobacco, tomatoes, vegetables and "other crops"; while for livestock: bovines and pigs. The "other credit" needs are also added to the total (for rural electrification, reforestation and flood plain management, etc.). Subsidized credit is an important element in the decision making process but historically only large farmers get it. The distance from the Municipio center and the farm is used as a proxy for the importance of location and region in the production decision. This variable is also used as an indicator of region specific soil / land quality. The average education level of the household is used as a proxy for access to information.

Table 3.5 lists the variable names and reports simple panel characteristics.

Table 3.5-Simple Panel Characteristics

Variable Description	Variable Name	Mean	Std. Deviation
Crop Production			
Quantity Index of Output	CQIN	448.11	745.79
Quantity Index of Modern Inputs	MODQIC	55.27	118.26
Quantity Index of Traditional Inputs	TRADQIC	9.81	22.87
Quantity Index of Labor Inputs	LABQIC	53.19	69.26
Livestock Production			
Quantity Index of Output	LQIN	286.96	666.72
Quantity Index of Modern Inputs	MODQIL	29.69	263.77
Quantity Index of Traditional Inputs	TRADQIL	51.94	156.8
Quantity Index of Labor Inputs	LABQIL	90.96	497.39
Infrastructural Variables			
Area Owned by Farmer	AFARM	33.88	38.33
Area of Farm Sharecropped	ASHARE	1.00	2.4
Area of Farm under Pasture	APAST	20.35	28.42
Area Under Cultivation	ACROP	7.514	8.109
Education of Household Head (yr.)	KEDUC	2.89	2.72
Distance from Municipio Center	DIST	22.46	13.61
Total Income from Off-farm work	TIOFJ	191092.46	1034896.86
Total Credit Received by farmer	RGTTK	3418.2	7681.56

NB. All land variables are in Hectares and all Income & Credit variables are in Cruzeiros.

We use here aggregate indices of price and quantity information is used. The unit of observation in the panel is the farmer. There are 384 farmers in each cross-section. The most pertinent feature of Table 3.5 is the large dispersion present in the panel output and input variables. The norm is mainly when the standard deviations are more than twice the mean. This immediately indicates the extent of diversity present in this group of farmers, both in terms of their yields and their use of inputs. This is not an unusual feature in developing countries where different sized farms adopt different tenurial practices and different production technologies. The variation seen in the panel with respect to tenancy status, farm size and input use is outlined in the following tables. This panel is representative of farms in Brazil which have varying characteristics and production technologies.

Table 3.6 gives variable descriptions for panel clusters based on a) Input Use and b) Tenancy status. For the purposes of this study, a small farm is one under 50 hectares while a large farm is over 50 hectares. Conventionally, a farmer operating on 10 hectares or less qualifies as a *minifúndio* and one operating over 1000 hectares is a *latifúndio*. The final panel contains 2226 observations. The three input categories leads to input clusters that are defined as RGM1 to RGM7, indicating the seven prevalent input combinations. Tenurial status is controlled between small and large farmers. The clusters for tenancy status depicted by KSH1-KSH5 depict the categories from full sharecropper (typically a small farmer), partial sharecroppers and full owners. Typically, a full sharecropper owns no land and sharecrops "in" while a partial sharecropper could either sharecrop "in" or "out". A tenant on someone else's farm is sharecropping "in" while a farmer renting out land for sharecropping purposes is sharecropping "out".

Table 3.6 Input Use Regimes

RGM1:	Modern, traditional & labor inputs
RGM2:	Modern & traditional inputs
RGM3:	Traditional & labor inputs
RGM4:	Labor & modern inputs
RGM5:	Own labor & traditional inputs
RGM6:	Own labor & modern inputs
RGM7:	Own labor & other "non-self" labor

Tenancy Status Regimes

KSH1:	Full sharecroppers -- own no land
KSH2:	Partial sharecroppers -- own ≤ 50 Ha.
KSH3:	Partial sharecroppers -- own > 50 Ha.
KSH4:	Full Owners – own ≤ 50 Ha. of land
KSH5:	Full Owners – own > 50 Ha. of land

Sharecropping is quite common in Brazil and Zona da Mata has about 50,000 landowners and 20,000 sharecroppers populating an area totaling 36,012 square kilometers. In Zona da Mata tenancy arrangements differ based on the farming methods adopted by the land owners. Table 3.7 represents some common tenancy contracts found in Zona da Mata.

Table 3.7-Sharecropping Arrangements

Cases	Inputs from Owner	Outputs for Owner	Farm Characteristics
I	all fertilizer & seeds	50%	cultivates annual crops
II	50%	33%	cultivates annual crops
III	50%	50%	coffee or tobacco cultivation
IV	25%	None	owner requires labor services for coffee or livestock production
V	None	None	

Source: Bradley (1990), pp. 50.

There are several indicators to imply that sharecropping "out" is one way to ensure availability of labor for the more lucrative production of coffee and livestock. This situation arises as most sharecroppers are relatively immobile with 38% continuing on the same farm for over 10 years which guarantees the landlord a stable supply of labor. The lower wage rate for sharecroppers than for hired labor makes it a cheap form of labor.

Table 3.8 indicates the trends of tenancy status in the two output categories. 26% of farmers in the panel engage in some form of sharecropping. There are full sharecroppers who own no land, partial sharecroppers who own land and sharecrop on some other individuals land and finally there are farmers who do not engage in any sharecropping activities.

Table 3.8 Tenancy Status Variation

	Crops % of farms in the regime	Livestock % of farms in the regime
Full Sharecroppers	11.59	10.39
Partial Sharecroppers	17.52	14.01
Full Owners	70.89	75.57

Although only 10- 11% of the farmers are full sharecroppers and about 14 - 18 % engage in some sharecropping activities, this still accounts for 24 - 29% of the farmers being subject to the tenurial constraints this method of farming entails. This makes it both informative and important to study the implications tenancy status might have on agricultural production and productivity.

Table 3.9 shows the variation in farm sizes although small farms predominate in Zona da Mata. One can see the negative correlation between farm size and sharecropping activities and the positive trend between farm size and production. 15.9% of the farmers in the panel have farms smaller than 5 hectares, 30.33% of the farms are less than 10 hectares, 52.34% are less than 20 hectares and 64.16% are less than 50 hectares. Only 28.62% of the total number of farms between 50 and 100 hectares and a mere 7.22% areas greater than 100 hectares. Almost 60% of the farms are less than 25 hectares and 77 % are less than 50 hectares.

Table 3.9-Farm Size Variation

Farm Size Range (hectares)	% of farms in Regime	% of Sharecropped land	Crop Production	Livestock Production
less than 1	0.175	34.48	27.67	47.8
Between 1 and 5	15.01	56.48	149.84	31.67
Between 5 and 10	15.14	31.41	235.92	63.93
Between 10 and 15	11.99	9.94	233.4	108.05
Between 15 and 20	10.02	4.59	348.86	154.53
Between 20 and 25	6.61	1.73	385.7	242.65
Between 25 and 30	5.21	2.99	366.84	188.56
Between 30 and 50	13.04	1.31	597.97	343.94
Between 50 and 75	9.41	0.09	844.79	712.87
Between 75 and 100	6.17	0.15	928.43	677
Greater than 100	7.22	0.04	1001.42	951.31

The different input bundles used in the production process can be seen in Table 3.10. With three input categories, there are seven separate input combinations. 89% of farms engaged in crop production use all three inputs, labor inputs in combination with modern inputs or only labor inputs. For livestock production, the most important input use regimes are where all three inputs are used and labor is used in tandem with traditional inputs. Recall, that absence of labor in any input-use category is interpreted as the farmer supplying only “own” or “self” labor.

Table 3.10-Input Use Variation

Combination of Inputs Used	Regime	% of farms in the regime Crops	% of farms in the regime Livestock
All Three Inputs	1	48.27%	68.72%
Modern & Traditional	2	2.81%	0%
Labor & Traditional	3	3.72%	29.79%
Modern & Labor	4	30.5%	0.45%
Only Traditional	5	1.04%	0.82%
Only Modern	6	1.57%	0%
Only Labor	7	10.47%	0.18%

Both tables 3.9 and 3.10 reveal the nature of the production algorithm that is pursued by most farmers: the percentage of land devoted to crops and pasture are a clear indication that farmers are diversified in their products.

Table 3.11 shows the mean panel characteristics for crop producers using different input bundles. Regimes 2, 1, 4 and 6 have the highest mean yields. All these high yield regimes use modern inputs. Regime 7 where only labor inputs are applied towards crop production, the mean yield is the smallest. It is also evident that in this regime, the smallest farms are present. About 10% of all crop producers are small farmers with low yields. This regime is important and is investigated in detail in Chapter 4 to see if tenurial status could be a driving force for the low levels of productivity. This would belie the empirical literature which indicates that the smaller farmers are often the most productive.

Table 3.11-Panel Means for Crop Production Under Different Input - Use Regimes

Regime	Output	Area in Farm (ha)	% of Area Cropped
1	532.7	41.98	21
2	593.6	78	13
3	249.7	31.9	16
4	478.32	21.2	32
5	263.02	54.1	11
6	408.16	33.1	19
7	170.34	10.9	36

For livestock production, the panel averages are presented for the two main regimes, namely 1 and 3. In regime 1 where all three inputs are used, the mean output is greater than that of regime 3 by a factor of 10. This would indicate that modern inputs make a big difference in rearing livestock versus when it is not used. Table 3.12 also reveals that it is the smaller farms that do not use any modern inputs and also devote a proportionately smaller percentage of their land to pasture.

Table 3.12-Panel Means for Livestock Production Under Different Input-Use Regimes

Regime	Output	Area in Farm (ha)	% in Pasture
1	437.91	45.9	64.16
3	41.51	10.35	26.59

Tables 3.13 A & 3.13 B depict the number of observations when the panel is stratified based on different input-use regimes and tenancy categories. For farmers engaged in crop production the first cell of Table 3.13 A indicates that 38 farmers use all three inputs and are full sharecroppers.

Table 3.13 A-Tenancy and Input-Use Patterns in Crop Production

	RGM1	RGM2	RGM3	RGM4	RGM5	RGM6	RGM7	
KSH1	38	0	22	92	0	0	111	263
KSH2	154	1	21	108	0	1	41	326
KSH3	10	1	0	1	0	0	0	12
KSH4	568	38	51	355	16	33	73	1134
KSH5	309	59	31	64	9	11	8	491
	1079	99	125	620	25	45	233	2226

Table 3.13 B-Tenancy Patterns in Livestock Production

	RGM1	RGM2	RGM3	RGM4	RGM5	RGM6	RGM7	
KSH1	30		207		6			243
KSH2	189	1	116	1	2		1	310
KSH3	11		1					12
KSH4	797		321	8	10		3	1139
KSH5	491		13	1				505
	1518	1	658	10	18	0	4	2209

The cell in the fourth row, fifth column contains 64 farmers who use labor and modern inputs. These 64 farmers are full-owners and own farms that are greater than 50 hectares. 89% of farmers engaged in crop production are in regimes 1, 4 or 7. Small farmers (with less than 50 Ha. of land) who do not engage in any sharecropping activities are the predominant crop producers. Full sharecroppers primarily use only labor inputs (RGM 7), while the majority of the large full-owners use all three inputs. Partial sharecroppers feature in the three main input-use categories for crop production: Regimes 1, 4 and 7, in that order of declining importance.

Table 3.13 B once again reiterates that the most important input use regimes for livestock production are 1 (where all three inputs are used) and 3 (where labor is used in tandem with traditional inputs). Livestock producers who are predominantly small full owners are once again the dominant tenurial category, with the majority using all three inputs. Farmers who are in regime 3 for input use are split almost evenly between being full owners and sharecroppers.

The diversity of the agricultural infrastructure of Brazil is captured in the Prodemata data set which is therefore representative of the Brazilian agricultural sector. This diversity is what makes analyses both interesting and difficult.

Efficiency and Productivity in Brazilian Agriculture

We next identify the magnitude and sources of productivity variations of the farmers in the Prodemata data set. The panel contains a predominance of small farmers who switch between input-use regimes from year to year. Along with the different input regimes prevalent in the production decisions of these farmers, they also differ in their tenancy status. The contention is that diverse ownership and input-use patterns affect production decisions and thereby efficiency levels. The methods used to derive the performance measures across different input-use and tenancy regimes include Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA).

Land is often the primary means of subsistence for rural Brazilians who predominantly compose of small farmers or *minifúndista* and to a lesser extent peasants with little or no access to land. In 1985, 52% of Brazilian farms had an area of less than 10 hectares. In the Prodemata data 30% of the farmers have less than 10 hectares of land. An interesting feature of Brazilian farms is the lack of correlation of small holdings with "traditional" agricultural production methods and large holdings with modern mechanized ones. It is an accepted reality that low levels of agricultural output persist among small farmers and rural landless laborers. Productivity enhancing methods in agriculture depends on the available technology and the conditions that govern its adoption. Incentives to improve productivity are strongly linked to the distribution of output. As a significant percentage producers own no land, they are dependent on the prevailing land tenure system to determine how the output gets distributed between the owners and agricultural labor. Sharecropping is a particularly common form of tenurial contracts in developing countries.

Sharecropping is a form of land tenancy where the landlord allows the tenant use of the land in lieu of a fixed fraction of the output (or share). Tenancy contracts may take on a variety of forms: from the landlord sharing in the non-labor costs to not contributing anything. If sharing of costs does take place there is nothing to indicate that it be proportional to the fraction of output received. Moreover, a number of restrictions may be placed on the tenant as to the type of crops grown, the amount of non-labor input supplied. The vast literature on this tenurial arrangement appears to stems from trying to "explain the persistence of an institutional arrangement that appears to be inefficient". The views on sharecropping have changed over the years: from being regarded as an inefficient arrangement to being considered an efficient one for risk sharing when other forms of insurance are not easily available. The prevailing view is that sharecropping provides a set of incentives to the farmer that is between those provided by rental (complete) and wage (none) contracts. Empirical studies on the productivity of sharecroppers have yielded contradictory results. Huang (1975) and Nabi (1986), using Malayan and Indian data respectively, agree with the hypothesis that sharecroppers are not inefficient while Shaban (1987) and Lee and Somwaru (1993), using Indian and US data respectively, reject the hypothesis. Lee and Somwaru report a surprising finding that the sharecroppers in the US are allocatively the least efficient but technically more efficient.

The Prodemata data reveals that approximately 30% of the farms in Zona da Mata engage in some form of tenurial practice. 10% are landless peasants while 17 % (engaged in crop production) are "partial" sharecroppers. Partial sharecroppers could be full owners leasing "out" land to others or leasing "in" additional land. Full sharecroppers are those with no land and are bound by all the contractual constraints that tenancy imposes. In the panel of crop producers, 12% are full sharecroppers. Of the 70% of farmers who do not sharecrop at all, 70% operate on small farms (defined as being less than or equal to 50 ha). The percentages of tenancy regimes for livestock production are similar. As tenurial practices differ, so may productivity across these different systems. Computing efficiency measures for different tenurial regimes would allow quantifying this effect.

Productivity or technical efficiency is defined as a firm's ability to produce maximum output given a level of inputs and technology. While a considerable literature has developed in the recent years to measure agricultural productivity in developing countries only a few have focused on Brazil. A majority of studies have used Indian agricultural data (Battesse et al., 1989, 1992a, 1992b, Bhattacharyya and Glover; 1993). Brazilian data is used by Taylor etal. (1986) to measure the efficiency of 433 farms. They find the average technical efficiency of total farm output to be 17%. Desai and Vosti (1989) use the Prodemata data to compute Data Envelopment Analysis (DEA) scores for farmers producing corn, rice and / or beans. They report that farmers who produce corn and rice have higher mean efficiency levels (0.52) than those producing some other combination of these three product categories. They do not account for how infrastructural characteristics could affect productivity levels.

We compute productivity measures for the Prodemata farmers using aggregate measures of crop and livestock production and include farm specific characteristics. Performance scores are initially computed for the entire unstratified panel. Efficiency measurement techniques assume homogeneity of inputs. The presence of different bundles of input-use and differing tenancy status cause this assumption to be violated. Moreover, labor inputs in agricultural production are not homogenous; self, family and hired labor are known to have differing degrees of productivity. To control for the heterogeneity that could stem from different input-use regimes and varying patterns of tenancy status, separate efficiency scores are computed for the different regimes.

Technical efficiency is computed using DEA and Stochastic Frontier Analysis (SFA), and compared within and across regimes and against the benchmark scores calculated for the entire panel. The motivation is to distinguish how various input-use categories perform vis a vis each other and examine whether tenancy status affects performance. An output-based Data Envelopment Analysis measure developed by Färe etal. (1990) and a time-varying Stochastic Frontier Analysis technique derived by Cornwell, Schmidt and Sickles (1990) is used to compute the performance measures. In addition, to ascertain the effect of decreased sample size on efficiency measures, we compute performance measures for random samples of dissimilar size. Finally we investigate the extent to which differences in soil quality can affect productivity. As land quality information is not available, we compute efficiency measures for five separate regions.

Methodologies

Schmidt (1985) noted the close relationship between the measurement of firm-level efficiency and the estimation of production functions[12]. The introduction of a production set by Koopmans and Debreu in 1950, has allowed the association of the interior of the set with its boundary. This enables one to distinguish between production processes that lie on the frontier from those that lie within the production set. The question this methodology illuminates is that if a firm produces 76% of its potential output, given its input usage, what is the maximum or 100% output level. Farrell's (1957) development of a measure of productive efficiency has allowed economists to evaluate how a firm's input and output levels contributes to its efficiency[13].

This efficiency measure is data based, in that each firm's representation is a point on an isoquant map or "reference set". This "reference set" can be described by a production technology **S.**

$$S = \left\{ (x, y) \mid x \in \Re_{+}^{J}, y \in \Re_{+}^{K}, (x, y) \text{is feasible} \right\} \qquad 3.1$$

where $x \in \boldsymbol{R}^{I}$ is a vector of quantities of **I** inputs and $U \in \boldsymbol{R}j$ a vector of quantities of **J** outputs that are feasible. The distance from any input-output combination of a decision making unit (DMU) to the frontier of the reference set is its measure of efficiency. This distance can be input or output based. A horizontal distance to the frontier, holding outputs constant yields an input-based measure which can be defined as ID:

$$ID(x, y) = \min\left\{ \lambda \mid (x / \lambda, y) \in S \right\} \qquad 3.2$$

Similarly, a vertical distance to the frontier holding inputs constant gives an output-based efficiency measure OD defined as

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[12] This section draws from Schmidt (1985); pp 290-292.

[13] Farrell's conceptual development of the measure was followed by an application to agricultural production in the United States in 1962.

$$OD(x, y) = \min\{\lambda \mid (x, y/\lambda) \in S\} \quad 3.3$$

An output or input efficient DMU has a value of 1 for these expressions while inefficient DMU's have efficiency scores less than 1.

The work of Koopmans, Debreu and Farrell has spawned what is today known as the efficiency literature: two broad categories of models can be distinguished in the literature depending on the use of deterministic or stochastic production frontiers. DEA models are non-parametric, deterministic models which use the linear programming techniques developed by Charnes, Cooper and Rhodes (1978) while the SFA models are parametric and use the stochastic frontier production functions independently developed by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977). Both these techniques use a "reference set" in computing measures of efficiency.

Non-Parametric Specification

DEA models try to find which DMU's create an "envelope surface" in the input-output space. This is akin to creating an empirical production function or a flexible piecewise linear approximation of the "best practice" reference technology. Technical efficiency for DMU's operating within this linear convex frontier is calculated by taking radial measures to it. DEA does not distinguish efficiency from noise. One of the appeals of DEA lies in its requirement of only quantity data. This empirical advantage is enhanced with neither the lack of cost minimizing or profit maximizing assumptions nor the specification of the underlying technology. These advantages are also cited as the methodology's shortcomings: the non-stochastic nature contaminates efficiency scores with omitted variables, measurement error and other sources of statistical noise.

We use the linear programming (LP) model of Färe etal. (1990) which is an output based DEA model for an intertemporal production set. This involves solving their LP for each DMU (x_{nt},

y_{nt}) for each time period to compute an output based technical efficiency measure. The specification of Färe etal. is shown below. We assume constant returns to scale by restricting the intensity weights z_{nt} to imply a convex polyhedral cone.

$$\left[OD\left(x_{nt}, y_{nt}\right)\right]^{-1} = \max \lambda_{nt} \qquad 3.4$$

subject to

$$\lambda_{nt} y_{knt} \le \sum_n \sum_t z_{nt} y_{knt} \qquad k = 1,...,K$$

$$\sum_n \sum_t z_{nt} x_{jnt} \le x_{jnt} \qquad j = 1,....,J$$

$$z_{nt} \ge 0 \qquad n = 1,...,N;\ t = 1,....,T$$

The solution to this LP gives a measure of how much a DMU can increase its output, holding inputs constant. An efficiency score of 0.4 would imply that given input levels, output can be radially expanded by 60%. An efficient DMU will have no slack in its output vector.

<u>Econometric Specification</u>

SFA models compare each DMU to an "average level" of technology rather than to an efficient frontier like DEA does. For a given combination of input levels, the realized production of a DMU is assumed to be bounded by a parametric function that is an *a priori* specification of the technology. This function composes of known inputs involving unknown parameters and a random error associated with measurement or noise. As SFA is based on statistical regression techniques, identification of efficiency requires the assumption of a specific distribution for the productive efficiencies in order to separate noise from efficiency. This causes SFA to be sensitive to *a priori* assumptions. While SFA's appeal lies in allowing standard statistical tests to be used, a major drawback is that the efficiency scores can be biased if the underlying technology is misspecified[14].

[14] Schmidt(1985), pp 296. He prefers this methodology over DEA as it allows standard types of statistical inferences.

To accommodate the advantages and disadvantages the parametric and non-parametric methods of efficiency measurement display, we also adopt the Cornwell, Schmidt and Sickles' (1990) or CSS model for comparison. The appeal of their SFA model over others is the introduction of time-varying coefficients over firms. This solves the unrealistic assumption of previous panel data models (Jondrow, Lovell, Materov and Schmidt; 1982 and Schmidt and Sickles; 1984) that efficiency scores are time-invariant. Panel SFA models relax the distributional assumptions on technical inefficiency and random noise and the assumption of independence between technical inefficiency and the explanatory variables that cross-sectional models impose. The CSS model introduces the time-varying nature of efficiencies by replacing the firm effect by a flexibly parameterized function of time with parameters that vary over firms. This allows output levels to vary over both firms and time. Following their terminology, a Cobb-Douglas specification with heterogeneity in the slopes and intercept can be expressed as:

$$y_{it} = \beta(x_{it}) + \gamma(z_{it}) + \alpha_i + \delta_i t + \varepsilon \qquad 3.5$$

where the subscripts i and t refer to firms and time respectively. The natural log of aggregate output is regressed on the inputs, the firm characteristics z_{it}, α the firm effect, δ_{it} a time effect and ε_t, the random error term. Efficiency measures stem from the variations in the cross-section as well as over time. This is derived from the residuals based on the within estimator. The α and δ coefficients capture the firm specific effects and are used to calculate the technical efficiency scores in each time period:

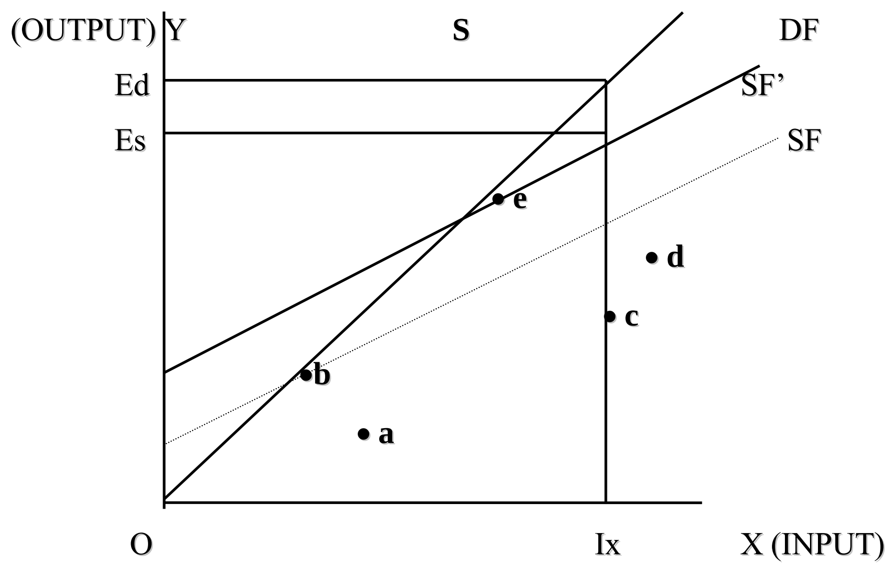
$$TE_{it} = \exp(\alpha_i + t * \delta_i) \qquad 3.6$$

Relative technical efficiency scores are obtained by normalizing the scores for the decision making units in each period to the most efficient one to get bounded scores between 0 and 1.

$$RTE_{it} = \frac{TE_{it}}{\max_t(TE_{it})} \qquad 3.7$$

The difference between the two methodologies is illustrated using a 5 DMU, one input, one output example where **S** is the "reference set". In Figure 3.1, the DEA frontier is DF, passing through efficient DMU's **b** and **e** (they make up the envelope). These DMU's have scores of 1. SFA efficiency scores are calculated by determining the most efficient DMU in each time period and setting its score to one. The "frontier" is created by shifting the estimated frontier (the dashed line SF) to pass through the most efficient DMU (**e** in this case) to SF'.

Figure 3.1-DEA vs. SFA



For example, DMU **c** has a DEA output based score of OEd/OIx < 1 (the vertical distance to the frontier). For this firm radial expansion of output is possible. DMU **c** has a relative SFA efficiency score of OEs/Ix <1. Thus both methods computes the fraction by which DMU **c** falls short of the respective frontiers.

As both DEA and SFA techniques are used to compute technical efficiency scores for the Prodemate panel, the measures need to be comparable. To do so, the DEA measures are regressed over all the variables used in the SFA regression. This additional step controls for additional regressors used in the SFA model. The predicted values from this regression are used as approximate measures of DEA performance. Like the SFA scores, the predicted DEA values are also re-normalized to the largest predicted value in each time period. This allows the two sets to be compared; which is achieved using Spearman's rank.

Results

DEA and SFA scores are initially computed for 3 cases. Case A calculates efficiency measures for the entire Prodemata panel, for crop and livestock production separately. Case B computes the performance measures controlling for different regimes of input-use. Case C investigates the effects of tenancy status on performance. As crop and livestock production are assumed to be separable, efficiency scores are computed separately for each output. The entire unstratified panel (Case A) is treated as the control group[15].

On examining the basis infrastructural variables across the different regimes of input-use and tenancy status; largest farms on average (AFARM) are owned by the farmers in KSH5 (the regime, which by definition contains large farm owners who engage in no sharecropping), followed by regimes RGME2 (farmers using modern and traditional inputs) and KSH2 (large farm owners who engage in partial sharecropping). The regimes KSH1 (full sharecroppers) and RGME7 have the smallest sized farms. These patterns are followed by ACROP, the area under cultivation and negatively correlated with ASHARE (the area sharecropped). KSH5 shows the highest average crop production (CQIN). The average levels of input-use are obviously correlated with the sample size in the different input-use regimes. KSH5 displays higher levels of use of modern and traditional inputs than other regimes. Along with input-use, area owned, area under cultivation, variables like education level of the household, amount of off-farm income earned and amount of credit received are also used in the computation of the efficiency scores.

Case A: Efficiency Measurement for the Entire Panel

The entire unstratified panel of 384 farmers followed over 6 time periods is used to construct DEA and SFA scores for crops and livestock separately. The panel and yearly average efficiency scores are reported in Table 3.14. The measures of predictive efficiency for the

[15] A cross analysis, where the regimes are controlled for input combinations and tenancy status, would be very informative, but lack of observations constrains that analysis.

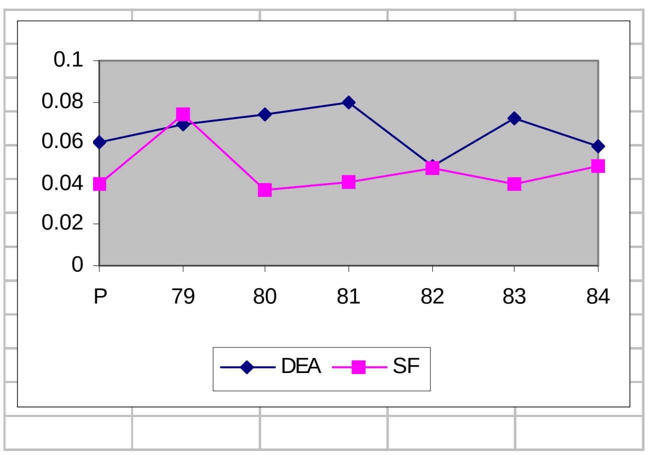
unstratified panel are extremely low with mean scores of 0.06 (DEA) and 0.04 (SFA). That is, the average farmer is 94% or 96% less efficient than those on the frontier. The median farmer has a DEA score of 0.04 and a SFA score of 0.05. Figure 3.2 depicts the time trend of the average scores. The productivity averages are uniformly low over the six year time period. The scores range between 5% (84) - 8%(81) mean efficiency for DEA and 3%(80)-. 7%(79) for SFA. The yearly trends show SFA scores be lower than DEA, on average, for all the years except 1979. The scores over the years are not trended together when one looks at the panel yearly averages: they diverge in 80,81 and 83.

Table 3.14-Panel Mean Efficiencies Grand Frontier

Year	P	79	80	81	82	83	84
DEA	0.06	0.069	0.074	0.08	0.049	0.072	0.058
SFA	0.04	0.074	0.037	0.041	0.048	0.040	0.049

*P represents panel.

Figure 3.2-Time Trend of Efficiency Scores-All Regimes



Spearman's Rank Correlation for Case A shows the tow measures of efficiency for the panel to be significantly correlated with a correlation coefficient of 0.6623. The variance between the two sets of scores is not high. Rank correlations by years, between DEA and SFA, are largest at 79% in 84 and smallest in 82 at 65%. These coefficients are higher than that for the entire panel.

This clearly indicates the importance of time effects on productivity. This is reasonable, as we know that production processes can change over time.

When the scores are sorted by DEA, the bottom 10% of the farmers have an average efficiency score of 0.0119 while the top 10% have an average score of 0.25. When the scores are sorted by the SFA measures, the top 10% has an average score of 0.18 while the bottom decile has a score of 0.007. There is obvious evidence of differences among farmers populating the two ends of the productivity spectrum. An interesting feature is the abysmal mean performance of the most efficient cohort. On comparing the characteristics for the extreme deciles, one finds AFARM (area owned) and ACROP (area cropped) in the top decile is about twice that of the bottom decile. This suggests large farmers with a greater proportion of cultivated land bring up the top end of the productivity horizon. TIOFJ (income earned from off-farm activities) is twice as much in the bottom decile (when sorting by DEA scores). This could imply that off-farm activities are driving down own farm productivity or perhaps more plausibly that off-farm activities are needed as a source of additional income (???). The scenario (when the scores are sorted by SFA) shows only a slight difference between average incomes earned from off-farm work between the top and bottom deciles and is in fact greater for the more efficient farmers. Land and tenancy patterns do not emerge as strikingly obvious factors that causes the productivity differences.

Table 3.15 gives the summary statistics for the distribution of these scores for the panel and for each year.

Table 3.15 Summary Statistics for Distribution of Efficiency Scores for Crops Grand Frontier

Panel	Mean	Variance	Skewness
DEA	0.06	0.008	5.67
SFA	0.04	0.006	8.67

DEA	**79**	**80**	**81**	**82**	**83**	**84**
Mean	0.069	0.074	0.08	0.049	0.072	0.058
Variance	0.009	0.008	0.009	0.006	0.008	0.008
Skewness	5.77	5.64	4.65	7.42	5.5	6.29

From Table 3.15 it is evident that the distribution of both DEA and SFA scores are right skewed, with the SFA scores being more so. The small variances suggest that most of the scores are clustered around the bottom of the distribution with only a few farms in the long right tails. A similar story emerges when we look at the distributions over time. The variances for the DEA scores are constant at 0.008 - 0.009 for all the years except 1982 when it drops slightly to 0.006. The distribution is most skewed for 1980. These distributions illustrate clearly that the majority of farms are clustered around a low efficiency level, with a very small number being scattered over the higher levels.

The obvious question is --what is driving these low efficiency scores? Why are the majority of farmers so inefficient compared to the few on the frontier? The factors that affect production are inputs, land (size and quality) and tenancy status. Farmers in the Prodemata data use different input-combinations, have differences in farm size (there is no soil quality data) and display varying tenancy status. These characteristics lead to different production patterns and levels of output. The question we pose is; are productivity levels being driven by these heterogeneous features? Production function analyses assume a homogenous technology across the units of analysis. Is homogenous technology determined by farm size, land quality, input use combinations or tenancy status? This is an important question, as production processes are a function of the underlying technology. Since the scores are relative measures, the comparison group needs to be relatively homogenous. Controlling for this heterogeneity is necessary to better approximate the underlying technology and make the comparison groups homogenous. This is the motivation for classifying the sample into sub-groups. The extremely low average scores could be linked to some heterogeneity not being captured by the processes generating the efficiency measures. If the comparison groups were made more homogenous, the efficiency measures would be more informative. Ceteris Paribus is a condition not being met when the entire panel is used to construct productivity measures. With the fixed effects approach used to compute efficiency scores, the inherent differences in land or soil quality is taken into account.

Case B: Efficiency Measurement --Different Input-Use Regimes

Both the literature and the data indicate that homogenous technology is best approximated by similar input combinations. The large differences in farmer-specific input matrices results from the presence of several zeros representing inputs not used and leads to a subsequent divergence in outputs. The following section constructs DEA and SFA efficiency measures for different input-use regimes and then tests the correlation of the observed scores viz. Case A and across methods. For crop production, cluster analysis is conducted for all seven input regimes and all five tenancy clusters but for livestock production only input-use clusters are investigated[16].

48% of farmers engaged in growing crops use all three inputs (RGME1), 30.5% use modern and labor inputs(RGME4) and 10.5% use only labor inputs(RGME7). The remaining 11% of the farmers are in regimes 2,3,5 and 6. Of these four regimes of input-use, only RGME3 has a labor component. The zero labor component simply means no “non-self” or family and/or hired labor. For Livestock Production: 68.72% of the farmers use all three inputs(RGME1) and 30% use labor and traditional inputs(RGME3). The remaining 1% of the farmers are in the other regimes of input use. Therefore it is important to focus on regimes 1, 4 and 7 for crop production and regimes 1 and 3 for livestock production.

For crop growers, 34.97% of the farmers (beside those in RGME1) use modern inputs either singly or in combination. This is interesting as most farmers are small with a prevalence of

[16] Stratifying the panel based on input use causes some observations to be lost. Moreover, for SFA scores, a minimum of 2 observations is needed. In order to accommodate this further observations are deleted.

sharecroppers. The larger farmers tend not to sharecrop "in" but often sharecrop "out". On closer inspection it is found that farmers with the least amount of sharecropped land use more of the modern inputs. This is consistent with previous findings. The ability to adopt modern inputs is theorized to be a function of farm size and thereby to credit.

The technical efficiency scores for the separate input-use regimes are presented in Table 3.16 for crop and livestock production.

Table 3.16 Panel Mean Efficiencies: Different Input-Use Regime Frontiers

Crops

Regime	1	2	3	4	5	6	7
DEA	0.25	0.54	0.29	0.28	0.58	0.59	0.32
SFA	0.18	0.22	0.23	0.20	0.65	0.48	0.31

Livestock

	1	3
DEA	0.29	0.22
SFA	0.17	0.26

Efficiency as measured by DEA (crop production), is highest for regimes 2, 5 and 6. These regimes together account for less than 6% of the panel and none employ labor that is measured as family and/or hired. Two possible explanations arise: one interpretation could be that "self" or "own" labor is more productive than family or hired labor, while the second is that the smaller sample size is responsible for this improvement. If the former is true, then it could be the cause of the higher scores in the regimes where no "non-self" labor is used. SFA also yields the highest scores for regimes 5 and 6. Regimes where family and/or hired labor is used are 1, 3, 4 and 7--all these regimes, irrespective of the method of scoring--show productivity measures around 20-30%. There appears to be a link between family and/or hired labor and lower productivity. The principal-agent problem is well documented: the hired hand has very low incentives to be productive while family members have a greater impetus to assist in increasing farm production levels.

For livestock production, efficiency measures are computed for regimes 1 and 3 as they comprise 99% of the panel. Both DEA and SFA measures yield mean panel efficiencies in the 20% range.

Once again, both regimes use "non-self" labor inputs. The average producer in the panel, whether he/she is producing crops or livestock, is 80% less efficient than the frontier producers.

The distribution of the scores reveals the extent of prevailing inefficiencies in each cluster. 70.4% in RGME1 have an efficiency score less than 0.25 (the panel average for the cluster). Similarly, 67.67% in RGME4 have scores less than 0.28 and 82.51% in RGME7 have a score less than the panel mean of 0.3. This divergence appears least in regimes 2, 5 and 6. RGME2 and RGME6 use modern inputs while RGME5 uses only traditional inputs. None of the regimes use "non-self" labor as an input. Once again, the divergence in efficiency scores may be an artifact of the differences in labor productivity or effort of family and hired labor. This does not seem implausible if one minds the fact that a considerable proportion of farmers engage in sharecropping activities. Tenancy could be driving the vast differences in productivity measures observed in the regimes where non-self labor is being used. For farmers engaged in the production of livestock, a very small percentage of farmers have efficiency scores greater than 0.5. In RGME1, 62.18% of the farmers have an efficiency score less than or equal to the panel mean while in RGME3, this disparity is more striking, with 81.03% of the farmers below the panel efficiency of 0.22.

The most overt feature of the frontier farmers in each of the regimes (Table 3.17) is that an overwhelming proportion are full owners who do not engage in any sharecropping activity. This holds true for both crop and livestock production.

Table 3.17 Salient Features of Frontier Farmers for Input-Use Regimes

Regime	1	2	3	4	5	6	7	1	3
							Crops		**Livestock**
Education levels	3.25	2.25	3.5	1.33	4	4.5	1.5	3	2.17
Area Sharecropped	0	0	0.39	0.7	0	0	45.1	0.84	3.26
crop production	1892.	918.9	470.2	506.7	270.2	379.9	741.89	531.0	48.18

The most efficient cohort in RGME1 (crops) is 75% more productive than the mean efficiency for the cluster and produce 262.34% more output. The frontier farmers in regimes 2 -7 are 46%, 71%, 72%, 42%, 41% and 70% more productive than the average farmer respectively. For livestock production, the frontier farmers are 71% more efficient than the average farmer in RGME1 and 78% more so in RGME3. A salient feature of the efficient farmers is that most are not sharecroppers and have on average a much smaller proportion of sharecropped area than the farmers in the cluster. In RGME7 (crop production) on average, 45.13% of the farmed land is sharecropped. This suggests that sharecroppers (who are subject to tenancy contracts) could be left skewing the distribution of efficiency scores. Only 2 of the frontier crop producers and one frontier livestock producer are full sharecroppers.

Spearman's correlation coefficient between the DEA and SFA scores for all regimes is highest for regimes 1, 2, 3 and 4 (crop production) with some aberrations, like the low insignificant coefficient in RGME2 for 1979. The correlation coefficients are not very high for livestock. In RGME1 the correlation is only of the order of 18% between the DEA and SF scores but jumps to about 45% for RGME3.

Several factors affect rural producers and their identification is a challenging task. Notwithstanding these obstacles, analyses are important, particularly for policy making. The rural decision maker is affected by institutionalized policies made at a macro-level. Effective policies need to incorporate the realities of rural production. This section has examined the efficiency of farmers in the region of Zona da Mata located in the state of Minas Gerais in Brazil. Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) are used to construct measures of efficiency. For this analysis a small farm is defined as having an area less than or equal to 50 hectares. In spite of the relative homogeneity in size, variability of several factors are observed: diversity of input-use and tenancy patterns are the most obvious. Seven separate input combinations and five distinct tenancy regimes(controlling for the size effect) are present.

Efficiency measures using the entire panel yield extremely low levels of mean productivity for the farms, with less than a half percent of the farmers possessing "the best practice technology". DEA and SFA scores are found to yield similar results. For this panel of farmers, low mean levels of technical efficiency are found to prevail. The majority of farmers are clustered on the lower end of the efficiency spectrum and are not in possession of the "best practice technology".

This suggests the presence of outliers but prior to estimation, the data had already been cleaned. The initial frontier, containing all farmers using diverse input combinations and participating in different tenancy schemes, is considered suspect. The inefficiencies were initially hypothesized to be driven by unaccounted heterogeneity. The source of this heterogeneity is assumed to stem from the varying input-use and tenancy patterns.

Frontiers constructed by clusters based on input-use regimes and tenancy patterns improve the mean levels of efficiency by 400%. Although this appears to be vast improvement, the average farmer in most clusters remains only 25-30% as efficient as the most "superior" producer. Imposing homogeneity via classifying the data alleviates some but not all of the heterogeneity problem. Some interesting results emerge from the cluster analyses: First and foremost, tenancy structures does not affect efficiency measures significantly. This is surprising as the panel comprises mainly of small farmers with prevalent tenurial systems running the entire gamut from full ownership to full sharecropper. Performance, of any tenancy category, is invariant to different frontiers of input-use. The second result is that while tenancy does not matter, input-use combinations affect productivity levels significantly and differently. Input-use regimes where only "self" labor is used in combination or in isolation of other inputs, have higher mean efficiencies than regimes where "non-self" labor like family and/or hired labor is used. This is evidenced as the principal-agent hypothesis. Thirdly, the productivity differences that exist between the "most efficient" farmers and the majority persist over time and across clusters.

Careful investigation of the characteristics of the "superior" or "best" farmers, in the panel and within every cluster, yield a single commonality shared by most of them: full ownership. These frontier farmers do not sharecrop "in" or "out". This result holds for the entire panel, for clusters where all three inputs are used and where modern and labor inputs are used. For farmers who use only labor (family/hired/self) in their production process the "best practice technology" is often operated by full sharecroppers. This finding is borne out by frontier farms for who are all in the "labor only" input regime. Finally, a very small proportion of the frontier farms are found to coincide across clusters.

In conclusion, this study acknowledges that, irrespective of the comparison group used to construct the frontier, vast differences persist in the farmers in possession of the "best practice technology" and the majority. This trend persists over time and across clusters. Classifying farms by input-use combinations seems to best approximate the underlying technologies. Smaller sample sizes that result from grouping similarly characterized farms leads to some of the observed efficiency improvements. Lack of soil-level and data could prove to be the missing link. The analysis of efficiency scores controlling for location of the farm seems to further support the notion that variability exists in soil quality. It is possible that the productivity differences exist only because the most efficient farmers are owners of the most fertile land, or are the most ideally situated in terms of irrigational access. If this were the case, then ownership of exceptional land could explain the efficiency difference between the frontier farms and the majority.

4. An Analysis of Selected Sectors in the Brazilian and Latin American Economies: The Recent Experience

As markets worldwide become less regulated, it becomes increasingly possible and timely to establish the presence of an empirical relationship between technical efficiency and market forces compelling agents to economize. Below we analyze key sectors in countries of Latin America, and in particular Brazil, to see if there is empirical support for such a conjecture during a period of unprecedented competitive pressures. We begin with a discussion of the methodology we will use to analyze manufacturing, agriculture and the services sectors in Brazil and in its Latin American competitors.

We take a relatively new approach to empirically examine the relationship between the competitive forces at play in Brazil and Latin America as these countries have opened up their economies to the discipline of international markets and the time pattern of technical efficiency. Our procedure is made possible by bringing together recent advances in various areas of the economics literature. In the technical efficiency arena, studies focused on cross-sectional results until developments in the panel estimation of technical efficiency (Schmidt and Sickles, 1984; Cornwell, Schmidt and Sickles, 1990) and generalizations of the linear programming approaches

(Tulkens and Vanden Eeckaut, 1995) allowed the recent exploitation of panel data sets. The ability to capture the dynamic nature of a firm's performance relative to its competitors has stimulated even greater interest in the topic. We outline the methodology below.

4.1 Dynamic Efficiency Measurement

Assume a panel with n=1,...,N firms, t=1,...,T periods, j=1,...,J inputs and k=1,...,K outputs. Thus, x_{jnt} is the level of input j used by firm n in period t and y_{knt} is the level of output k produced by firm n in period t. Further, assume an intertemporal production set where input and output observations from all time periods are used. The production technology, **S**, is **S** = {(x, y) | x ∈ $\Re^J_+$, y ∈ $\Re^K_+$, (x, y) is feasible}.

The efficiency scores are the distances from the frontier. An output-based distance function, OD, is defined as OD(x,y) = min{λ | (x, y/λ) ∈ **S**}.

The intertemporal output-based efficiency score is obtained from the following linear programming model:

(4.1)

$$[OD(x_{nt},y_{nt})]^{-1} = \max \lambda_{nt}$$

subject to

$$\lambda_{nt}\, y_{knt} \leq \Sigma_n \Sigma_t\, w_{nt}\, y_{knt}, \qquad k = 1,...,K,$$

$$\Sigma_n \Sigma_t\, w_{nt} x_{jnt} \leq x_{jnt}, \qquad j = 1,...,J,$$

$$w_{nt} \geq 0, \qquad n = 1,...,N;\ t = 1,...,T$$

where the condition on the weights, w_{nt}, gives constant returns to scale (CRS).

The efficiency results obtained from DEA can be regressed[17] on a matrix of firm characteristics

[17] Since the dependent variable (either DEA or FDH scores) is bounded by 0 and 1, it is censored. The problem is one of single censoring since there are several cases where technical efficiency equals 1 but no cases where the score

including firm specific intercepts and time trends.[18] The residuals from this regression provide another measure of performance since they capture the efficiency score conditioned on these other characteristics.

Nonparametric analysis of productivity growth's decomposition into technical change and catch-up necessitates the use of a contemporaneous version of the data. The production technology, output distance function and DEA linear programming problem (Equations (1)-(3)) are amended such that input-output combinations from only period *t* are used. In addition, the productivity index requires output distance functions calculated between periods. $OD_t(x_{t+1}, y_{t+1})=\min\{\lambda \mid (x_{t+1}, y_{t+1}/\lambda.\in \mathbf{S}_t\}$ has the technology of time *t* and scales outputs in time *t+1* such that (x_{t+1}, y_{t+1}) is feasible in period *t*. The observed input-output combination may not have been possible in time *t*; hence, the value of this expression can exceed one that would represent technical change. Similarly,

$$OD_{t+1}(x_t, y_t)= \min\{\lambda \mid (x_t, y_t/\lambda.\in \mathbf{S}_{t+1}\}$$

has the technology of time *t+1* and scales outputs in time *t* such that (x_t, y_t) is feasible in period *t+1*. The final equation can be expressed as follows:

$$M(x_{t+1}, y_{t+1}, x_t, y_t)=\frac{OD_{t+1}(x_{t+1},y_{t+1})}{OD_t(x_t,y_t)} * \left\{\frac{OD_t(x_{t+1},y_{t+1})}{OD_{t+1}(x_{t+1},y_{t+1})}\ \frac{OD_t(x_t,y_t)}{OD_{t+1}(x_t,y_t)}\right\}^{1/2} = E_{t+1} * A_{t+1} \quad (4.2)$$

This index captures the dynamics of productivity change by incorporating data from two

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is 0. To account for this, tobit analysis is performed. Correlations between the second stage OLS regressions and the tobit regressions are very high.

[18] This second stage regression is necessary to control for differences in input and output characteristics since, under DEA and FDH, only inputs and outputs can be included in the initial calculations. Note that under SF the characteristics as well as the time and firm dummies are simply included in the original translog functional form.

adjacent periods: E_{t+1}, reflects changes in relative efficiency while A_{t+1}, reflects changes in technology between t and $t+1$. For the index, a value below 1 indicates productivity decline while a value exceeding 1 indicates growth. Similarly, for the index components, values below 1 signify a performance decline while values above 1 signify an improvement.

4.2. Growth results for Latin America, Chile, Brazil, and Mexico

We intended to analyze the growth experience of LA countries and Brazil (as well as Chile and Mexico, two of the growth outliers in LA) at the sector level by modeling the multiple outputs at the country level as manufacturing, agriculture, and services output. Inputs were labor, energy, and investment. Our data come from the World Development Indicators (2002). Unfortunately, the individual country levels in these sectors showed so little relative variation around trend that we were unable to estimate meaningful production relationships with the disaggregated sectoral data. Instead we analyzed aggregate performance of GDP, the aggregate of these sectoral outputs. We first analyze a Cobb-Douglas model of aggregate production allowing for Solow-type productivity change. We estimate a separate production function for each country and for the pooled sample of all LA countries. Then we estimate technical efficiency for each country in 1980, 1990, and 2000. The countries are ranked and the change in ranking is analyzed. We turn to any evidence that the economy of Brazil, a country that considers itself to be the most similar to countries in the OECD (which includes Mexico), has separated itself from the pack of other LA countries during the 1990's? A similar analysis of Mexico and Chile is also provided. Finally, we compute by how much could LA in general and Brazil and Mexico in particular increase output per worker were it operating at a technically efficient level in 1980, 1990, and 2000.

Results for the constant returns to scale Cobb-Douglas production function with Hicks-neutral productivity growth using the sample of all Latin American countries are found in Table 4.1. The findings indicates that on average during the period 1971-2000 development of the economies in Latin America was largely due to capital and energy inputs with relatively low labor productivity. Total factor productivity grew at an annual rate of about 1.1 percent. If we examine the most dynamic economies of the region, Chile, Brazil, and Mexico, separately we find similar results over the period for TPF growth in Mexico and Brazil (1.2 and 1.3 percent/year). These results are in Tables 4.2-4.4. However, Chile's growth appears to be completely due to the intensive marginal use of capital, energy, and labor inputs. Labor productivity seems most pronounced in Chile, followed by Mexico and Brazil.

Table 4.1 Productivity Growth For Latin American Countries: 1971-2000

Results of multiple regression for log(Y/L)

Summary measures

Multiple R	0.9299
R-Square	0.8646
Adj R-square	0.8638
StErr of Est	0.2519

ANOVA Table

Source	df	SS	MS	F	p-value
Explained	3	192.8746	64.2915	1013.5090	0.0000
Unexplained	476	30.1949	0.0634		

Regression coefficients

	Coefficient	Std Err	t-value	p-value	Lower limit	Upper limit
Constant	2.2595	0.5022	4.4990	0.0000	1.2727	3.2463
log(K/L)	0.6840	0.0263	26.0242	0.0000	0.6323	0.7356
log(E/L)	0.2981	0.0421	7.0821	0.0000	0.2154	0.3809
time	0.0111	0.0017	6.5171	0.0000	0.0077	0.0144

Table 4.2 Productivity Growth For Chile: 1971-2000

Summary measures

Multiple R	0.9433
R-Square	0.8898
Adj R-Square	0.8771
StErr of Est	0.1720

ANOVA Table

Source	df	SS	MS	F	p-value
Explained	3	6.2155	2.0718	70.0108	0.0000
Unexplained	26	0.7694	0.0296		

Regression coefficients

	Coefficient	Std Err	t-value	p-value	Lower limit	Upper limit
Constant	2.7622	2.9205	0.9458	0.3530	-3.2409	8.7653
log(K/L)	0.5994	0.1310	4.5746	0.0001	0.3301	0.8687
log(E/L)	0.1844	0.3069	0.6008	0.5531	-0.4465	0.8153
time	0.0025	0.0083	0.3030	0.7643	-0.0146	0.0196

Table 4.3 Productivity Growth For Brazil: 1971-2000

Summary measures

Multiple R	0.9786
R-Square	0.9576
Adj R-Square	0.9527
StErr of Est	0.1106

ANOVA Table

Source	Df	SS	MS	F	p-value
Explained	3	7.1710	2.3903	195.5451	0.0000
Unexplained	26	0.3178	0.0122		

Regression coefficients

	Coefficient	Std Err	t-value	p-value	Lower limit	Upper limit
Constant	4.6083	4.0092	1.1494	0.2608	-3.6327	12.8492
log(K/L)	0.7105	0.0867	8.1913	0.0000	0.5322	0.8889
log(E/L)	0.7277	0.5602	1.2990	0.2053	-0.4238	1.8791
Time	0.0132	0.0053	2.4727	0.0203	0.0022	0.0241

Table 4.4 Productivity Growth For Mexico: 1971-2000

Summary measures

Multiple R	0.9525
R-Square	0.9073
Adj R-Square	0.8966
StErr of Est	0.1531

ANOVA Table

Source	df	SS	MS	F	p-value
Explained	3	5.9623	1.9874	84.8085	0.0000
Unexplained	26	0.6093	0.0234		

Regression coefficients

	Coefficient	Std Err	t-value	p-value	Lower limit	Upper limit
Constant	2.2476	2.9460	0.7629	0.4524	-3.8080	8.3032
log(K/L)	0.6601	0.1175	5.6183	0.0000	0.4186	0.9016
log(E/L)	0.2555	0.3410	0.7493	0.4604	-0.4454	0.9563
time	0.0124	0.0059	2.1183	0.0439	0.0004	0.0245

We next turn our attention to the linear programming results and begin with a focus on the level of technical efficiency for each country at the end of each decade of the sample period covered in our sample, 1980, 1990, and 2000. These results are in Table 4.5 and are reported in terms of the country rankings within Latin America. The significant changes were in Nicaragua and

Argentina. Nicaragua started with the highest technical efficiency in the 80s, but by 2000 had the worst technical efficiency of all LA countries. Argentina started out as the 9th ranked country but moved into the lead in both 1990 and 2000 (See Table 4.5).

As far as GDP, Brazil has always had the largest, but in 1990, other LA countries were close behind. By 1997 Brazil's GDP was more than double that of any other LA country. In this sense it did pull away from the other countries, although by 1999 other countries were closing in again. As for technical efficiency, Brazil was in the middle of the pack for the entire 1990s, a stagnant response to the international market incentives that presumably were driving market reforms in other parts of Latin America. Mexico also remained in the middle of the distribution of Latin American countries in terms of technical efficiency. Its GDP growth remained fairly stable as well. In 1980, 1990, and 2000, the technical efficiencies for Brazil and Mexico respectively were, 0.567, 0.963, 0.604 and 0.988, 0.746, 0.820. Therefore Brazil could have increased output per worker by 43.3%, 3.7%, and 39.6% in those years, while Mexico could have increased by 1.2%, 25.5%, and 18% in those years, had they operated at a technically efficient level.

Table 4.6: Decompositions of Dynamic TFP Change for Brazil, Mexico, and All Latin America

Year	country	effch	techch	tfpch	year	country	effch	techch	tfpch
1980	Brazil	0.777	1.325	1.029	1990	Brazil	0.963	1.102	1.061
1981	Brazil	1.548	0.724	1.12	1991	Brazil	0.735	1.174	0.863
1982	Brazil	1.017	1.033	1.051	1992	Brazil	0.873	1.092	0.953
1983	Brazil	0.842	0.87	0.732	1993	Brazil	1.165	0.92	1.072
1984	Brazil	1.15	0.893	1.027	1994	Brazil	0.969	1.13	1.094
1985	Brazil	0.891	1.066	0.95	1995	Brazil	1.067	1.066	1.138
1986	Brazil	1.012	1.133	1.146	1996	Brazil	1.023	1.045	1.069
1987	Brazil	0.967	1.045	1.01	1997	Brazil	0.995	1.031	1.026
1988	Brazil	1.051	1.027	1.08	1998	Brazil	0.926	1.006	0.932
1989	Brazil	1.262	1.024	1.292	1999	Brazil	0.656	1.05	0.689
		1.0517	**1.014**	**1.0437**			**0.9372**	**1.0616**	**0.9897**

Year	country	effch	techch	tfpch	year	country	effch	techch	tfpch
1980	Mexico	1.053	1.334	1.404	1990	Mexico	0.746	1.51	1.127
1981	Mexico	1.012	1.009	1.021	1991	Mexico	0.886	1.325	1.174
1982	Mexico	0.74	0.821	0.607	1992	Mexico	1.021	1.024	1.046
1983	Mexico	0.816	1.091	0.89	1993	Mexico	1.304	0.822	1.072
1984	Mexico	1.656	0.74	1.226	1994	Mexico	0.896	1.054	0.945
1985	Mexico	0.843	1.11	0.936	1995	Mexico	0.842	1.034	0.87
1986	Mexico	0.618	1.155	0.714	1996	Mexico	0.906	1.047	0.949
1987	Mexico	1.494	0.859	1.282	1997	Mexico	0.979	0.989	0.968
1988	Mexico	1.087	1.039	1.13	1998	Mexico	1.197	0.93	1.114
1989	Mexico	1.181	0.878	1.037	1999	Mexico	1.058	1.139	1.205
		1.05	**1.0036**	**1.0247**			**0.9835**	**1.0874**	**1.047**

Year	country	effch	techch	tfpch	year	country	effch	techch	tfpch
1980	all	0.861	1.28	1.102	1990	all	0.943	1.265	1.193
1981	all	1.114	0.832	0.927	1991	all	1.089	0.936	1.019
1982	all	1.011	0.997	1.008	1992	all	0.994	0.993	0.988
1983	all	1.01	0.997	1.006	1993	all	1.068	0.88	0.94
1984	all	1.059	0.89	0.943	1994	all	0.919	1.126	1.034
1985	all	0.857	1.085	0.93	1995	all	0.997	1.033	1.03
1986	all	0.905	1.111	1.005	1996	all	0.984	1.017	1.001
1987	all	1.047	0.956	1.001	1997	all	1.03	0.969	0.998
1988	all	0.949	0.977	0.927	1998	all	1.056	0.877	0.926
1989	all	0.954	1.033	0.986	1999	all	0.861	1.241	1.068
		0.9767	**1.0158**	**0.9835**			**0.9941**	**1.0337**	**1.0197**

Average Total productivity growth for Brazil, Mexico, and all LA countries is found in Table 4.6. In the 80s, all LA countries decreased their TFP with an average change, of 0.9835, while in the nineties they improved averaging 1.0197. Mexico outperformed the average TFP, improving TFP in the 80s, and by an even greater amount in the 90s, with values of 1.0247, and 1.047 respectively. Brazil reversed the trend in other LA countries. In the 80s they had a positive change, with a value of 1.0437 in the 80s, actually outperforming Mexico, while in the 90s the fell to .9897 averaging a negative change, while the rest of LA experienced positive change.

5. Concluding Remarks

This research has taken an integrated approach to analyzing the sources of growth in the Latin American economies in general and selected countries such as Brazil in particular. We have examined growth prospects with a careful eye toward the prospects of the countries of Latin American displaying any evidence that their challenge of competing with the advanced economies of the OECD is a thing of the past. Although we do find evidence of particular successes in particular time periods, we find no evidence of a systematic trend using a battery of methods for the emergence of Brazil or any other country in Latin American as a new competitor for scarce resources such as oil, other than those that accompany modest growth with relatively low labor productivity.

References

Abramovitz, M. (1986), "Catching up, Forging Ahead and Falling Behind," *Journal of Economic History*, 46, 385-406.

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

Baer, W.(1989), *The Brazilian Economy: Growth and Development*, Praeger, New York.

Barro, R. J. (1990), "Government Spending in a Simple Model of Endogenous Growth," *Journal of Political Economy*, 98, 103-25.

Barro, R.J. (1991), "Economic Growth in a Cross Section of Countries," *Quarterly Journal of Economics,* 106, 408-443.

Barro, R.J. and Sala-i-Martin, X.(1993), *Economic Growth*, *mimeo,* Harvard University, Cambridge, Mass.

Barth, J., Keleher, R., and Russek, F. (1987), "The Scale of Government and Economic Activity," *mimeo*.

Battese, G.E., Coelli, T.J. and Colby, T.C. (1989), "Estimation of Frontier Production Functions ans Efficiencies of Indian Farms Using Panel Data from ICRISAT's Village Level Studies," *Journal of Quantitative Economics,* 5, 327-48.

Battese, G.E. and Tessema, G.A. (1992a), " Estimation of Stochastic Frontier Production Functions with Time-Varying Parameters and Technical Efficiencies Using Panel Data form Indian Village," Revised version of paper presented at the 36th Annual Conference of the Australian Agricultural Economics Society at the Australian National University.

Battese, G.E. and Coelli, T.J. (1992b), " Frontier Production Function, Technical Efficiency and Panel Data: With the Application to Paddy Farmers in India," *Journal of Productivity Analysis,* 3, 153-69.

Baumol, W.J. (1986), "Productivity Growth, Convergence and Welfare: What the Long-Term Data Show," *American Economic Review*, 76, 1072-85.

Baumol, W.J., Blackman, S.A.B. and Wolff, E.N. (1989), *Productivity and American Leadership*, *The Long View*, M.I.T. Press, Cambridge, Mass.

Baumol, W.J. and Wolff, E.N. (1988), "Productivity Growth, Convergence and Welfare: Reply," *American Economic Review*, 1155 et seq.

Bhaduri, A. (1973), " A Study in Agricultural Backwardness Under Semi-Feudalism," *Economic Journal*, 34, 120-137.

Bhattacharyya, A. and Glover, T.F.(1993), " Profit Inefficiency of Indian Farms: A System Approach," *Journal of Productivity Analysis,* 4,391-417.

Bradley, T.(1990), "*Factor affecting the Use of Modern Agricultural Technology: A Case Study of Zona de Mata, Minas Gerais, Brazil, 1979-84,"* Ph.D Dissertation, University of Pennsylvania, PA.

Busom, I. and Nerlove, M. (1986) , "An Empirical Study of the Determinants of the Adoption of New Agricultural Inputs: Preliminary Results, " *mimeo*, University of Pennsylvania and International Food Policy Research Institute.

Charnes, A., Cooper, W.W., and Rhodes, E. (1978), "Measuring the Efficiency of Decision Making Units," *European Journal of Operational Research* , 11(1), 429-444

Cooley, T.F. and LeRoy, S.F. (1981), "Identification and Estimation of Money Demand," *American Economic Review,* 71, 825-844.

Cornwell,C., Schmidt, P., and Sickles, R.C. (1990), "Production Frontiers with Cross-Sectional and Time Series Variation in Efficiency Levels," *Journal of Econometrics*, 46, 185-200.

De Long, J.B. (1988), "Productivity Growth, Convergence and Welfare: Comment," *American Economic Review*, 78, 1138-1154.

Denison, E.F. (1962), "The Sources of Economic Growth in the United States and the Alternatives Before Us," *Committee for Economic Development*, Washington, DC.

Denison, E.F. (1979), "Accounting for Slower Economic Growth: The United States in the 1970's," *The Brookings Institute,* Washington, DC.

Desai, A. and Vosti, S.A.(1989), "Efficiency among Output-Diversified Farmers in Brazil's Zona da Mata: A Multiple-Input, Multiple-Output Application of DEA," Paper presented at the Conference of New Uses of DEA in Management, UT Austin.

Dix, R.H. (1992), "Military Coups and Military Rule in Latin America," *mimeo,* Rice University.

Dowrick, S. and Nguyen, D-T (1989), "OECD Comparative Economic Growth, 1950-85: Catch-Up and Convergence," *American Economic Review*, 79, 1010-1030.

Edwards, S.(1989), "Openness, Outward Orientation, Trade Liberalization and Economic Performance in Developing Countries," *World Bank Working Paper Series* No. 191.

Färe, R., Grosskopf, S., Lovell, C.A.K., and Yaisawarng, S.(1990), "Derivation of virtual Prices for Undesirable Outputs: A Distance Function Approach", forthcoming, *Review of Economics and Statistics*.

Farrell, M.J. (1957), " The Measurement of Productivity Efficiency," *Journal of the Royal Statistical Society,* Series A, 120/3, p. 253.

Feder, G. (1983), "On Exports and Economic Growth," *Journal of Development Economics,* 12, 59-74.

Friedman, M. (1977), “Inflation and Unemployment,” *Journal of Political Economy*, 85, 451-472.

Grier, K.B. and Tullock, G.,(1989) "An empirical Analysis of Cross-National Economic Growth, 1951-1980," *Journal of Monetary Economics,* 24, 259-276.

Huang, Y. (1975), “Tenancay Patterns, Productivity and Rentals in Malaysia,” *Economic Development and Cultural Change,* 23(4), 703-718.

Hultberg, P., M. I. Nadiri, and R. C. Sickles (1999), “Technology Adoption and Efficiency,” *Annales d’Economie et de Statistique, Special Issue on the Econometrics of Panel Data*, 55-56, 449-474.

Hultberg, P., and R. C. Sickles (2001), “Convergent Economies: Implications For World Energy Use,” in *Unlocking the Assets: Energy and the Future of Central Asia and the Caucasus: A Political, Economic, and Cultural Analysis*, A. Jaffe et al. (ed.), Macmillan Publishing Co., 2001.

Hultberg, P., M. I. Nadiri, and R. C. Sickles (2002), “Heterogeneous Rates of Catch-Up in Manufacturing Industries,” Rice University, mimeo.

Jondrow, J., Lovell, C.A.K., Materov, I.S., and Schmidt, P.(1982), “ On the Estimation of Technical Inefficiency in the Stochastic Frontier Production Function Model,” *Journal of Econometrics* , 19(2/3), 233-238

Kormendi, R.C. and Meguire, P.G. (1985), "Macroeconomic Determinants of Growth: Cross-Country Evidence," *Journal of Monetary Economics,* 16, 141-163.

Landau, D. (1983), "Government Expenditure and Economic Growth: A Cross-Country Study," *Southern Economic Journal*, 49, 783-792.

Lee, H and Somwaru, A. (1993), “The Measurement of Productive Efficiency: Techniques and Applications” in *The Measurement of Productive Efficiency: Techniques and Applications*, ed., Fried, H.O., Lovell, C.A.K and Schmidt, S.S., Oxford University Press, 188-299.

Levine, R. and Renelt D. (1992), “ A Sensitivity Analysis of Cross-Country Growth Regressions”, *American Economic Review,* 82(4), pp. 942-963.

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

Mellor, J. and Ahmed, R. eds.(1988), *Agricultural Price Policy for Developing Countries*, Johns Hopkins University Press, Baltimore.

Nabi, I. (1986), "Contracts, Resouce Use and Productivity in Sharecropping," *Journal of Development Studies,* 22(2), 429-442.

Nerlove, M., (1986), *The Use of Modern Inputs in the Agricultural Sectors of Developing Countries: The Case of Brazil*, *mimeo*, University of Pennsylvania and International Food Policy Research Institute.

Nerlove, M., Sickles, R.C. and Vosti, S.(1990) "On the Adoption of New Technology in Traditional Agricultural Sectors: The Zona Da Mata Region of Brazil, 1979-1984," *mimeo*.

Nerlove, M. and Vosti, S.A.(1987), "The Use of Modern Inputs in the Zona da Mata, Brazil: An Analysis of Covariance Structures Model, A Progress Report," International Food Policy Research Institute, Washington D.C.

Nerlove, M., Vosti, S. and Basel, W., (1989), "Role of Product Mix and Farm-Level Diversification in Adoption of Modern Technology: The Case of the Zona da Mata of Minas Gerais, Brazil," *mimeo*.

Newberry, D. (1975), "Tenurial Obstacles to Innovation," *Journal of Development Studies*, 11, 263-277.

Ram, R. (1986), "Government Size and Economic Growth: A New Framework and Some Evidence from Cross-Section and Time Series Data," *American Economic Review*, 76, 1991-203.

Romer, P.M. (1990a), "Capital, Labor, and Productivity," *Brooking Papers on Economic Activity*, special issue, 337-420.

Romer, P.M. (1990b), "Endogenous Technological Change," *Journal of Political Economy*, part 2, 98, 71-102.

Scandizzo, P.L. (1979), "Implications of Sharecropping for Technology Design in Northeast Brazil, " in Economics and the Design of Small-Farmer Technology, Edited by A. Valdes, G. Scobie and J. Dillon, Iowa State University Press, Ames.

Schmidt, P. (1985), "Frontier Production Functions," *Econometric Reviews*, Vol 4., No.2, 289-328.

Schmidt, P. and Sickles, R.C.(1984), "Production Functions and Panel Data," *Journal of Business and Economic Statistics*, 2, 367-374

Schuh, E.G.(1970), *The Agricultural Development of Brazil*, Praeger Publishers.

Schultz, T.W. (1964), *Transforming Traditional Agriculture*, Yale University Press, New Haven, CT.

Shaban, A. (1987), "Testing between Competing Model of Sharecropping," *Journal of Political Economy,* 95(5), 893-920.

Stockman, A.C. (1981), "Anticipated Inflation and the Capital Stock in a Cash-in-advance Economy," *Journal of Monetary Economics,* 8, 387-393.

Summers, R. and Heston, A. (1984), "Improved International Comparison of Real Product and Its Composition: 1950-80," *The Review of Income and Wealth,* 30, 207-262.

Summers, R. and Heston, A. (1988), "A New Set of International Comparisons of Real Product and Price Levels: Estimates for 130 Countries," *The Review of Income and Wealth,* 34, 1-25.

Summers, R. and Heston, A. (1991), "The Penn World Table (Mark 5): An Expanded Set of International Comparison, 1950-1988," *Quarterly Journal of Economics*, 327-368.

Taylor, T., Drummond, H. and Gomes, A.,(1986), " Agricultural Credit Programs and Production Efficiency: An Analysis of Traditional Farming in Southeastern Minas Gerais, Brazil," *American Journal of Agricultural Economics*, 110-119

Tulkens, H and vanden Eeckaut, P. (1991), " Non-parametric Efficiency Measurement for Panel Data: Methodologies and an FDH Application to Retail Banking," *CORE working paper.*

UNESCO Statistical Yearbook, New York, NY., various issues.

World Bank National Accounts, Washington, DC: World Bank, various years.

Table 4.5: Country Rankings of Technical Efficiency at the end of each decade of the sample period (1971-2000)

	Country	1980 t	1990 t	2000 t		Country	1980 t	1990 t	2000 t		Country	1980 t	1990 t	2000 t
1	Nicaragua	1	0.392	0.316	1	Argentina	0.71	1	1	1	Argentina	0.71	1	1
2	Uruguay	1	1	1	2	Uruguay	1	1	1	2	Uruguay	1	1	1
3	Venezuela, RB	1	0.828	1	3	Brazil	0.567	0.963	0.604	3	Venezuela, RB	1	0.828	1
4	Mexico	0.988	0.746	0.82	4	Venezuela, RB	1	0.828	1	4	Mexico	0.988	0.746	0.82
5	El Salvador	0.953	0.602	0.7	5	Costa Rica	0.823	0.769	0.786	5	Guatemala	0.882	0.528	0.818
6	Guatemala	0.882	0.528	0.818	6	Peru	0.562	0.759	0.555	6	Costa Rica	0.823	0.769	0.786
7	Costa Rica	0.823	0.769	0.786	7	Mexico	0.988	0.746	0.82	7	El Salvador	0.953	0.602	0.7
8	Chile	0.817	0.648	0.595	8	Chile	0.817	0.648	0.595	8	Brazil	0.567	0.963	0.604
9	Argentina	0.71	1	1	9	El Salvador	0.953	0.602	0.7	9	Chile	0.817	0.648	0.595
10	Colombia	0.7	0.487	0.465	10	Guatemala	0.882	0.528	0.818	10	Dominican Republic	0.588	0.476	0.585
11	Dominican Republic	0.588	0.476	0.585	11	Ecuador	0.588	0.492	0.406	11	Peru	0.562	0.759	0.555
12	Ecuador	0.588	0.492	0.406	12	Paraguay	0.569	0.491	0.462	12	Colombia	0.7	0.487	0.465
13	Paraguay	0.569	0.491	0.462	13	Colombia	0.7	0.487	0.465	13	Paraguay	0.569	0.491	0.462
14	Brazil	0.567	0.963	0.604	14	Dominican Republic	0.588	0.476	0.585	14	Ecuador	0.588	0.492	0.406
15	Honduras	0.564	0.354	0.359	15	Nicaragua	1	0.392	0.316	15	Honduras	0.564	0.354	0.359
16	Peru	0.562	0.759	0.555	16	Honduras	0.564	0.354	0.359	16	Nicaragua	1	0.392	0.316
	total	0.77	0.66	0.65										

Appendix I-Trend Estimates of Per Capita GDP in 18 L.A.

The data comes from Summers and Heston (1991). Each country's series of real per capita GDP ($PGDP_{it}$ i =1,...,18, t =1950,...,1988) is given in constant dollars (1985 international prices). The $PGDP_{it}$ trend growth rates are estimated by the following model:

$$ln PGDP_{it} = \alpha_0 + \alpha_1 t + \alpha_2 t^2 + \alpha_3 t^3 + \alpha_4 t^4 + \varepsilon_{it} \qquad 1950 \le t \le 1960$$
$$ln PGDP_{it} = \beta_0 + \beta_1 t + \beta_2 t^2 + \beta_3 t^3 + \beta_4 t^4 + \varepsilon_{it} \qquad 1960 \le t \le 1973$$
$$ln PGDP_{it} = \gamma_0 + \gamma_1 t + \gamma_2 t^2 + \gamma_3 t^3 + \gamma_4 t^4 + \varepsilon_{it} \qquad 1973 \le t \le 1987$$

Imposing continuity for the whole time period, we estimated the following piece-wise continuos polynomial function

$$\begin{aligned} ln PGDP_{it} = {} & \delta_0 + \delta_1 t + \delta_2 d_1 (t - t_1^*) + \delta_3 d_2 (t - t_2^*) \\ & + \delta_4 t^2 + \delta_5 d_1 (t - t_1^*)^2 + \delta_6 d_2 (t - t_2^*)^2 \\ & + \delta_7 t^3 + \delta_8 d_1 (t - t_1^*)^3 + \delta_9 d_2 (t - t_2^*)^3 \\ & + \delta_{10} t^4 + \delta_{11} d_1 (t - t_1^*)^4 + \delta_{12} d_2 (t - t_2^*)^4 + \varepsilon_{it} \end{aligned} \qquad (I.1)$$

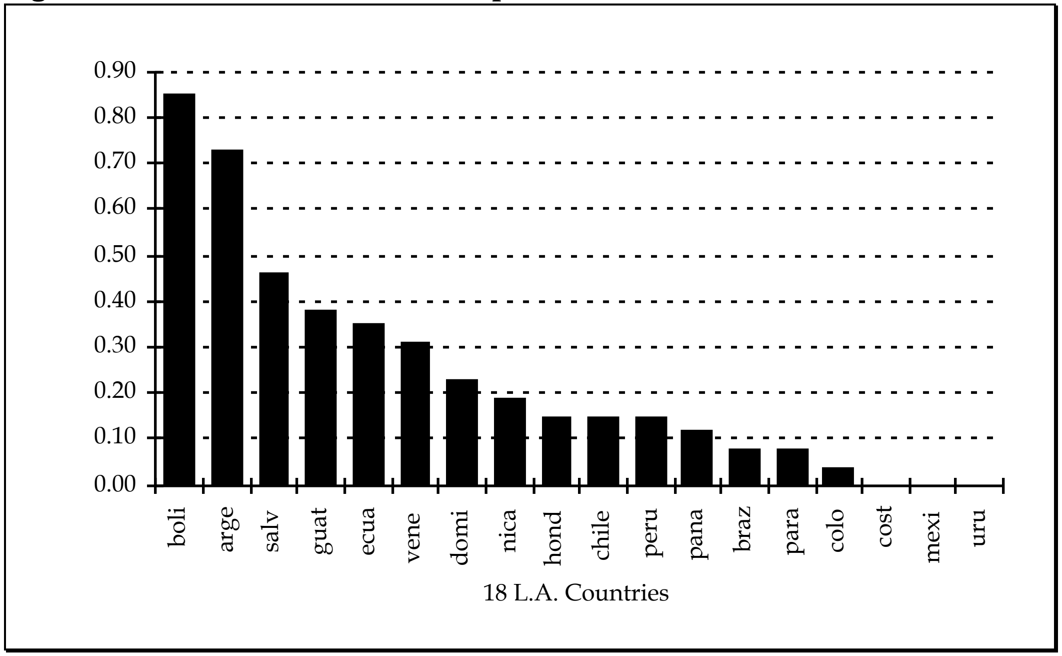
where,

$d_1 = 1$ if $t \ge t_1^*$; $t_1^* = 1960$
$d_2 = 1$ if $t \ge t_2^*$; $t_2^* = 1973$.

The estimated trend ($RGDP$) and observed levels $PGDP$ of are listed in Table I.1 for 1950, 1960, 1973 and 1987. These estimated trend values come from the antilogarithms of the predicted values by estimation I.1. The standard errors of the estimations of $ln PGDP_{it}$ from I.1 are listed in Table I.2. These standard errors measure the deviation of a trend growth path of $ln PGDP_{it}$ a results of business cycles and other fluctuations. The growth rate trend estimates are given by the coefficients in regression I.1. The standard error of these coefficients indicate the error in measuring growth rates based on the actual rather than trend estimates of $lnPGDP_{it}$ levels at the beginning of each period.

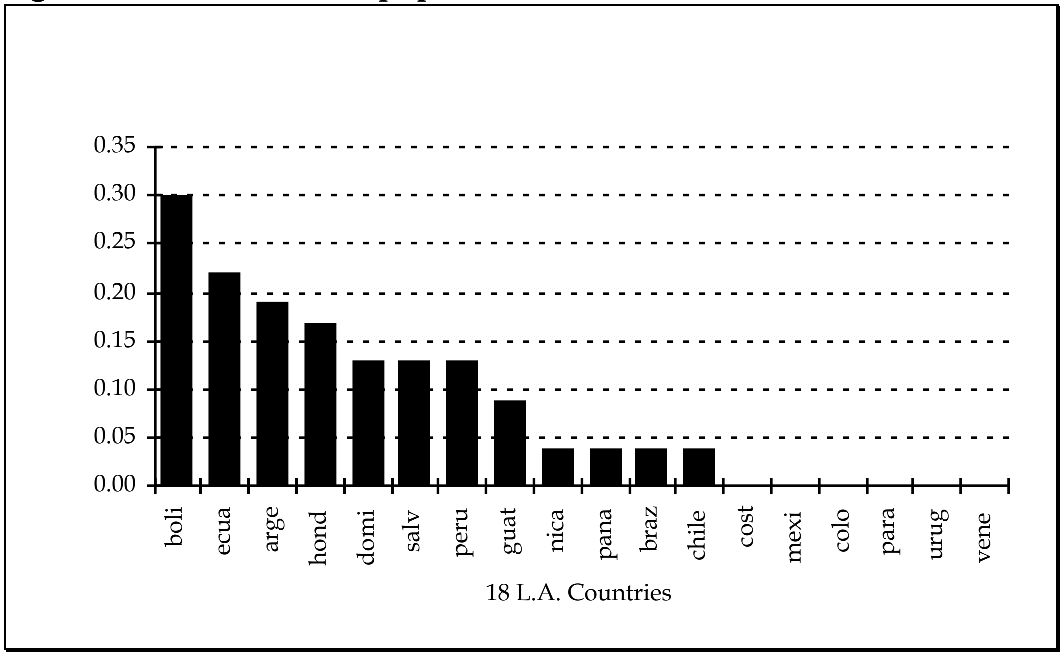
Appendix II–Political Instability Indices

Figure II.1–Number of Revolutions per Year in 18 L.A., 1960-87



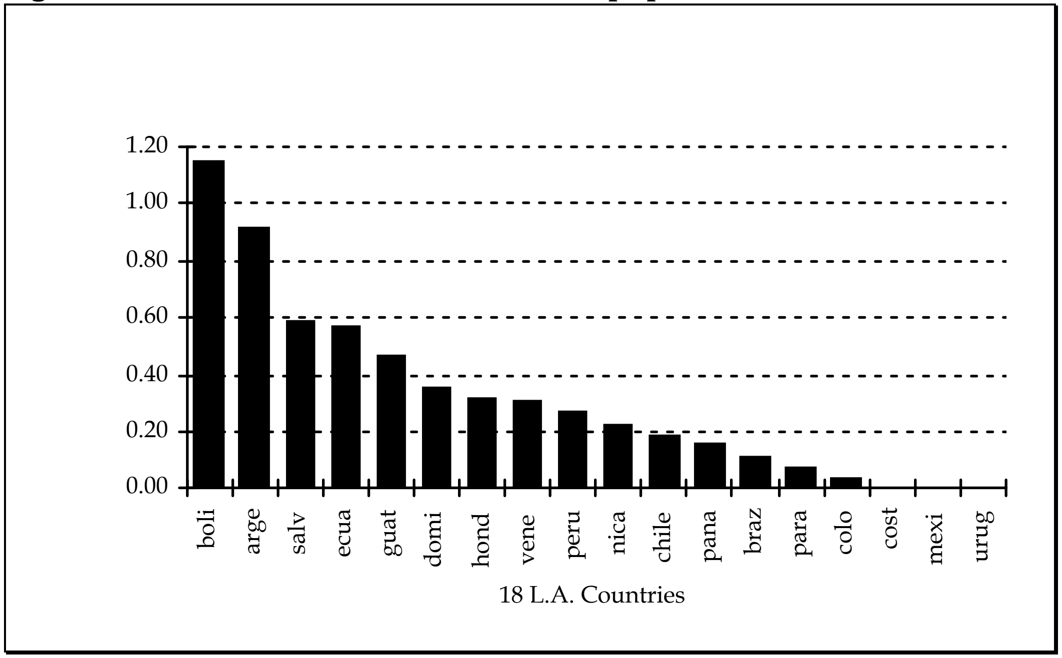
Data Source: Barro (1991).

Figure II.2–Number of Coups per Year in 18 L.A., 1960-87



Data Source: Barro (1991).

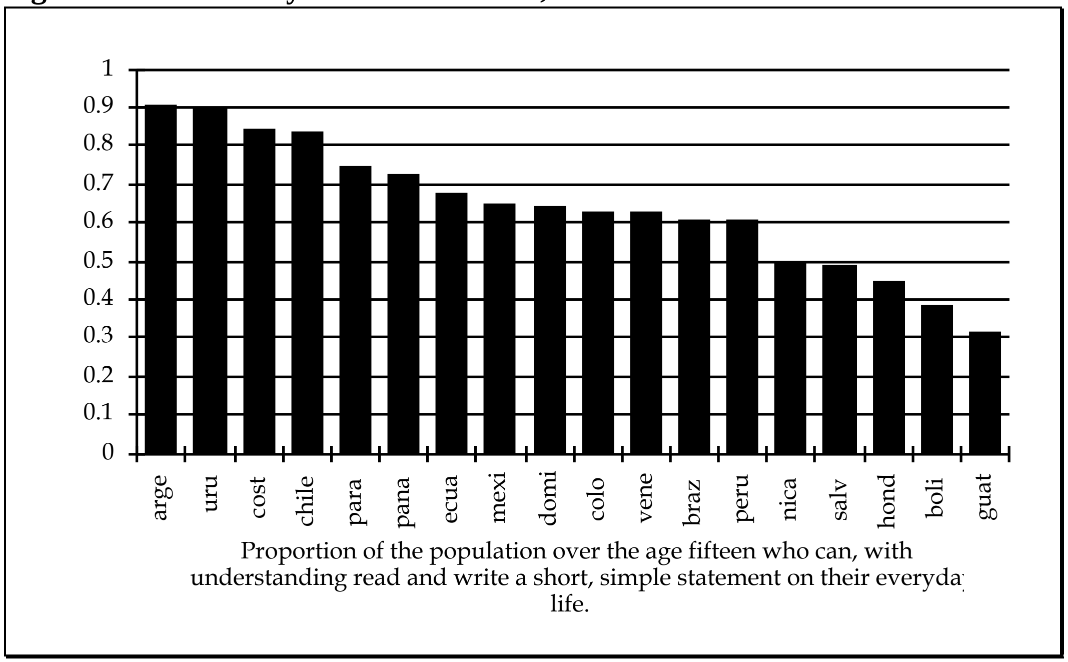
Figure II.3–Number of Revolutions and Coups per Year in 18 L.A., 1960-87



Data Source: Barro (1991).

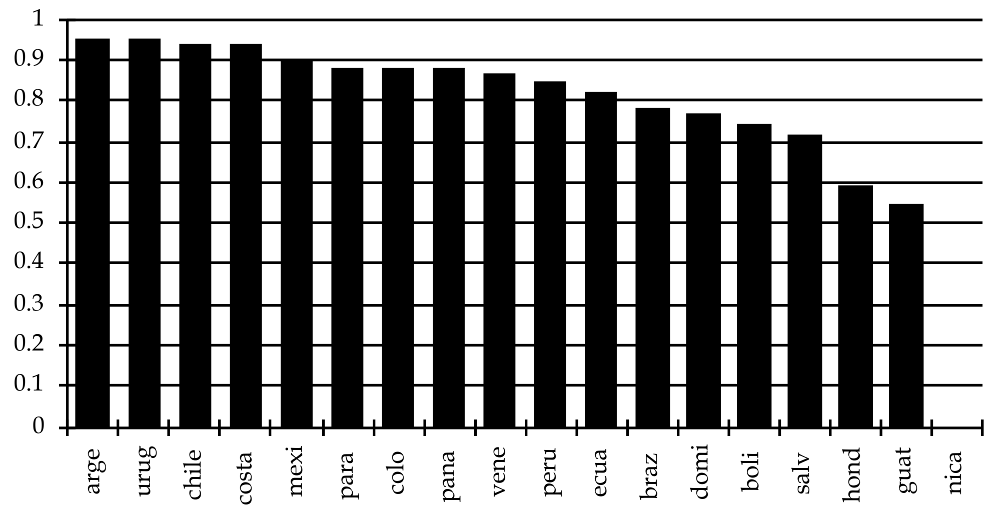
Appendix III–School-Enrollment and Literacy Rates Indices

Figure III.1– Literacy Ratios in 18 L.A., 1960.



Data Source: World Bank World Tables, various editions.

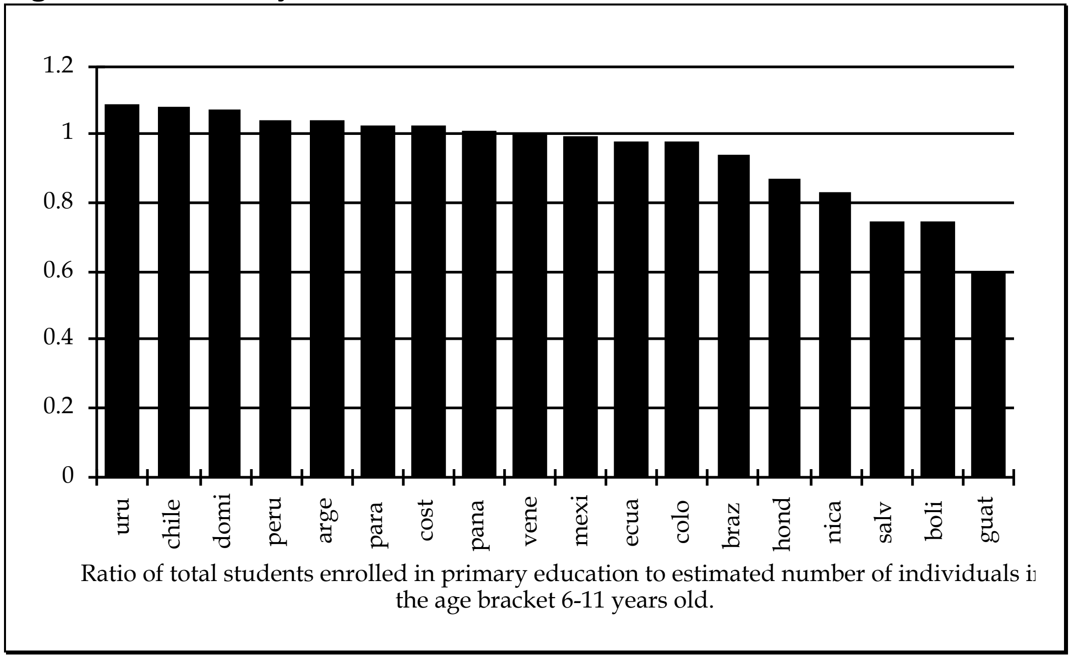
Figure III.2–Literacy Ratios in 18 LA., 1985.



Proportion of the population over the age fifteen who can, with understanding read and write a short, simple statement on their everyday life.

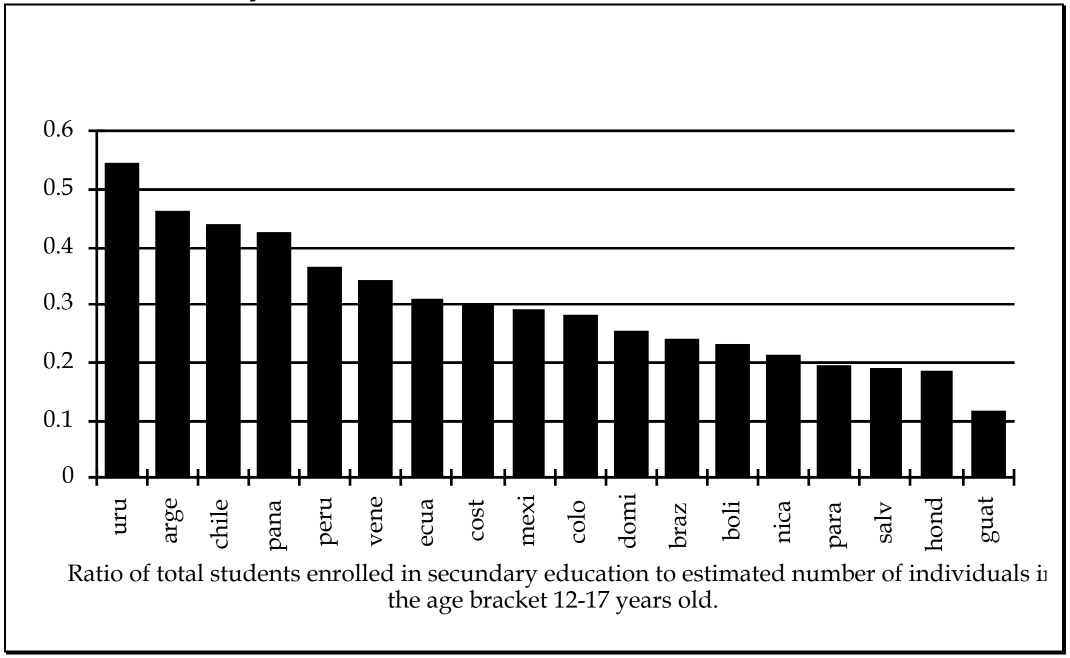
Data Source: World Bank World Tables, various edition.

Figure III.3–Primary Education in 18 L.A., 1960-85.



Data Source:World Bank World Tables, various editions.

Figure III.4–Secundary Education in 18 L.A., 1960-85.



Data Source:World Bank World Tables, various editions.

Appendix IV–Definition of Variables and Data Sources

BMP — Black Market Exchange Rate Premium.
Source: Levine and Renelt (1992).

EAP — Economically Active Population.
Source: Summers and Heston (1991), and CEPAL (Comision Economica para America Latina y el Caribe).

GR6087 — Average Growth of Real Gross Domestic Product, 1960-87.
Source: Summers and Heston (1991).

GOV — Government Consumption Share of Real Gross Domestic Product.
Source: Levine and Renelt (1992).

GSG — Growth of the Share of Government Consumption (GOV).
Source: Levine and Renelt (1992).

I/Q — Investment Share of Real Gross Domestic Product.
Source: Summers and Heston (1991).

LIT — Adult Literacy Rate in 1960.
Source: Barro (1991).

PI — Average Inflation of GDP Deflactor.
Source: Levine and Renelt (1992).

PRGDP — Real Per Capita Gross Domestic Product.
Source: Summers and Heston (1991).

PRIM60	Primary School-Enrollment Rate 1960. *Source:* Barro (1991).
REV	Number of Revolutions Per Year, 1960-1987. *Source:* Barro (1991).
RGDP##	Trend Estimates Levels of Real Per Capita Gross Domestic Product, in 19##. *Source:* Summers and Heston (1991).
RGDP6087	Average Growth of Real Per Capita Gross Domestic Product, 1960-1987. *Source:* Summers and Heston (1991).
SEC60	Secondary School-Enrollment Rate 1960. *Source:* Barro (1991).
STPI	Standard Deviation of Inflation (PI). *Source:* Levine and Renelt (1992).
X	Exports Share of Real Gross Domestic Product. *Source:* Levine and Renelt (1992).
Yt	Logarithm of RGDP Level, Relative to U.S. RGDP in period t. *Source:* Summers and Heston (1991).