On the Nature of Income Inequality Across Nations*

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Abstract

In this paper, we investigate the nature of income inequality across nations by first estimating, testing, and distinguishing between two types of aggregate production functions: the extended neoclassical model and a mincerian formulation of schooling-returns to skills. Next, given our panel-data estimates, we proceed in decomposing the variance of the (log) level of output per-worker in 1985 into that of three distinct factors: productivity, human capital, and the dynamic incentives to accumulate capital. Finally, we classify a group of 95 countries according to their relative position (above or below average) for each of these factors. The picture that emerges from these last two exercises is one where countries grew in the past for different reasons, which should be considered for policy design. Although there is not a single-factor explanation for the difference in output per-worker across nations, it seems that productivity differences can explain a considerable portion of income inequality, followed second by dynamic inefficiencies and third by human capital accumulation.

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1 Introduction

The focus of the literature on economic growth has changed from the early-day studies of differences in growth rates among countries (e.g., Barro(1991)) to studies that try to understand the differences in the level of output per worker among countries. For a given country, since the level of output per worker can be thought as its cumulative growth experience, studying it is equivalent to studying long-run growth. Indeed, differences of output per worker across countries are very high, which illustrates that the their long-run growth experience has been very diverse. For example, in 1990, the average worker in the U.S. produced 34 times more than a worker in Mali, 12 times more than a worker in Guyana or India, and twice as much as a worker in Portugal.

In recent years, a number of studies have tried to explain these differences. Their results can be roughly divided into two groups. The first finds that differences in factors of production alone (e.g., physical and human capital) can explain most of the observed differences in output per worker; see for example, Mankiw, Romer, and Weil(1992), Chari, Kehoe, and McGrattan(1997), and Mankiw(1995). The second group finds that, even controlling for physical and human capital, there is still a large portion of output per worker disparity left unexplained. Hence, total factor productivity (TFP) disparity can be a crucial determinant of output per worker differences across countries; see, for example, Hall and Jones(1999), Prescott(1998), and Klenow and Rodriguez-Clare(1997).

The conclusions in these articles are somewhat influenced by their methodological choices, particularly by the choice of the functional form of the aggregate production function, by the choice of the estimation method and/or by the parameter-calibration employed. For example, Mankiw, Romer and Weil assume that, apart from OLS-residual variation, productivity is the same across countries. Thus, the importance of factors is automatically strengthen. On the other hand, Hall and Jones work with a production function where human capital is not a separate input, but only modifies raw labor. Hence, they have only two factors, and not three: physical capital and labor. Moreover, they calibrate the physical-capital share to be relatively small and equal to $1/3$. All these choices automatically reinforce the role of productivity.

Since these methodological choices can potentially drive the final results obtained, we think that one way to avoid this problem, being neutral on methodological issues, is to test the specification being used. Hence, we propose using a pragmatic approach: instead of assuming a priori a specific aggregate production function, two alternative functional forms are estimated. The first is a model with a long tradition in the growth literature - the extended neoclassical growth model proposed by Mankiw Romer and Weil, among others. The second is a mincerian formulation of schooling-returns to skills, traditionally used in the labor-economics literature, e.g., Mincer(1974) and Wills(1986), but recently incorporated into the growth literature as well, e.g., Bills and Klenow(1996), and Hall and Jones(1999). After estimating these two sets of regressions, we ask which of these two specifications best fits the data using a variety of specification tests. The restriction that productivity is the same across countries is not imposed a priori, but rather tested using a panel-data set of 95 countries, ranging from 1960 to 1985, extracted from the Summers and Heston (1991) and the Barro and Lee (1996) data bases.

After considering the results of specification tests, and choosing which production-function best represents the data, productivity and factor-share estimates are used to study the contribution of factors of production, productivity, and dynamic distortions in explaining the variation of output per worker. These dynamic distortions are tax-distortions affecting the return on physical capital, calculated following Chari, Kehoe, and McGrattan (1997). For each country, they were calibrated to make the modified golden rule hold in equilibrium, using estimated factor shares, TFPs, and the stock of physical and human capital per worker.

Our preferred panel-regression equation uses the mincerian specification with an estimated capital share of about 42%, a marginal return to education of about 7.5% per year, and an estimated productivity growth of about 1.4% per year. Our productivity estimates are very different across countries, with a ratio of the highest-to-the-lowest greater than four. Testing whether productivity is the same across countries strongly rejects this hypothesis.

Using regression results, and calibrated tax-distortions, the variability of output per worker was explained in terms of three components: human capital, productivity, and dynamic distortions (i.e., tax distortions affecting the return of capital). A variance decomposition exercise shows that productivity and the dynamic distortion are the most important factors in explaining the variation in output per worker across countries. Productivity explains 53%, while the dynamic distortions explains 24%.

Finally, we divided the set of 95 countries into 8 sub-sets, according to their relative position with respect to the average of the three determinant factors of output per worker. As expected, the set of countries with above-average productivity and education, and below-average dynamic distortions, contains almost all of the rich countries. On the other extreme, the set of countries with below-average productivity and education, and above-average dynamic distortions, contains only poor nations, with average output per worker of about one tenth of that of the rich-country group. The remaining groups have either one or two factors above average.

The results showed that all ex-communist countries had high human capital and little distortions, but were amongst the least productive economies overall. For example, Romania had the smallest productivity estimate of all countries, which was more than four times smaller than the U.S.-productivity estimate. Also, Japan, Taiwan, and Korea are low-distortion and high-education countries, but their productivity levels are below-average for world standards: Korea's estimated TFP is only 56% of that of the U.S. Hence, we reproduce here Young's (1995) result that the good performance of these countries in the recent past was mostly due to factor accumulation and not high productivity.

Despite the importance of productivity in explaining the dispersion of output per worker in our sample of countries, it may be unimportant as a factor hampering long-run growth for some specific countries. For example, Brazil and

Uruguay have almost the same output per worker (1/4 of the U.S. level) and productivity, but the labor force in Brazil has about half the schooling of that in Uruguay, and Uruguay's distortion to capital accumulation is more than 20% higher than in Brazil. This shows that these countries should pursue different development policies to reduce the gap between them and the group of rich nations.

Taken together, the evidence here shows that: (i) according to econometric tests, productivity cannot be modelled as being the same for all countries. Moreover, differences in productivity cannot be disregarded as an explanation of why output per worker varies so much across countries; (ii) despite that, there is not a single factor that can explain why output per worker varies so much across countries. This becomes obvious once countries are classified according to their relative attributes in terms of productivity, human capital and dynamic distortions. Hence, a uniform policy to foster growth is bound to be ineffective, since country specificities have to be taken into account in designing them.

This paper has five additional Sections. In Section 2 we discuss the functional forms used to run production-function panel regressions. In Section 3, the econometric techniques and the specification tests used are discussed. In Section 4 we present estimation results. Section 5 is on the nature of income inequality across nations, and Section 6 concludes.

2 Model Specification

The first production function considered here is the so-called "extended neoclassical model," which uses human capital as an additional explanation for output, jointly with physical capital and raw labor. We follow, among others, Mankiw, Romer and Weil (1992). Start with the following homogenous-of-degree-one production function:

$$Y_{it} = A_{it} F\left(K_{it}; H_{it}; L_{it} \exp(g \cdot t)\right); \qquad (1)$$

where Y_{it}, K_{it}, H_{it}, L_{it}, and A_{it} are respectively output, physical capital, human capital, raw labor inputs, and productivity for country i in period t, where $i = 1; \cdots; N$, and $t = 1; \cdots; T$. It is assumed that there is exogenous technological progress at rate g which is the same across countries. The production function in per-worker terms can be written as:

$$\frac{Y_{it}}{L_{it}} = y_{it} = A_{it} F\left(k_{it}; k_{it}; \exp(g \cdot t)\right): \qquad (2)$$

Assuming Cobb-Douglas technology (or using a first-order log-linear approximation of the above function) gives:

$$\ln y_{it} = \ln A_{it} + \alpha \ln k_{it} + \beta \ln h_{it} + \gamma g \cdot t + \varepsilon_{it}; \qquad (3)$$

where ε_{it} is the inherited measurement error for country i in period t. Imposing homogeneity (i.e., $\gamma = (1 - \alpha - \beta)$), we obtain the following:

$$
\begin{aligned}
\ln y_{it} &= \ln A_{it} + \alpha \ln k_{it} + \beta \ln h_{it} + (1 - \alpha - \beta) g \cdot t + \varepsilon_{it} \\
\ln y_{it} &= \ln A_{i} + \alpha \ln k_{it} + \beta \ln h_{it} + (1 - \alpha - \beta) g \cdot t + \eta_{it},
\end{aligned} \qquad (4)
$$

where in the last line A_{it} is decomposed into a time-invariant component A_i and a component that varies across i and t - ν_{it}, such that $\eta_{it} = \nu_{it} + \varepsilon_{it}$. Due to the symmetric treatment of the factors, the extended neoclassical production function strengthens the importance of inputs vis-a-vis productivity in explaining output per-worker dispersion. Moreover, the higher the income share of accumulated factors, the higher is the income disparity across countries that can be explained by inputs.

The second specification differs from the above in the way human capital is modelled. It uses a mincerian (e.g., Mincer(1974) and Wills(1986)) formulation of schooling-returns to skills to model human capital. Although it is traditionally used in work on labor-economics, it has been recently incorporated into the growth literature as well, e.g., Bills and Klenow(1996), and Hall and Jones(1998). There is only one type of labor in the economy, which has skill-level θ, determined by educational attainment. It is assumed that the skill-level of a worker with h years of schooling is $\exp(\phi h)$ greater than that of a worker with no education at all, leading to the following homogenous-of-degree-one production function:

$$Y_{it} = A_{it} F\left(K_{it}, \theta_{it} L_{it} \exp(g \cdot t)\right). \qquad (5)$$

The parameter ϕ in $\theta_{it} = \exp(\phi h_{it})$ gives the skill-return of one extra year of education. In per-worker terms, the equation above reduces to:

$$\frac{Y_{it}}{L_{it}} = y_{it} = A_{it} F\left(k_{it}, \theta_{it} \exp(g \cdot t)\right). \qquad (6)$$

Again, with Cobb-Douglas technology (or with a first order log-linear approximation of the production function) we obtain:

$$\ln y_{it} = \ln A_{it} + \alpha \ln k_{it} + \beta \ln\left(\theta_{it} \exp(g \cdot t)\right) + \varepsilon_{it}. \qquad (7)$$

where ε_{it} is the inherited measurement error for country i in period t. Finally using $\theta_{it} = \exp(\phi h_{it})$ and imposing homogeneity (i.e., $\beta = 1 - \alpha$), we obtain:

$$
\begin{aligned}
\ln y_{it} &= \ln A_{it} + \alpha \ln k_{it} + (1 - \alpha)(\phi h_{it} + g \cdot t) + \varepsilon_{it} \\
\ln y_{it} &= \ln A_{i} + \alpha \ln k_{it} + (1 - \alpha)(\phi h_{it} + g \cdot t) + \eta_{it},
\end{aligned} \qquad (8)
$$

where, again, in the last line, in the last line A_{it} is decomposed into a time-invariant component A_i and a component that varies across i and t - ν_{it}, such that $\eta_{it} = \nu_{it} + \varepsilon_{it}$. The mincerian formulation strengthens the importance of productivity vis-a-vis inputs in explaining output per-worker dispersion. This happens because human capital is not a separate factor of production, but only augments labor productivity.

The basic difference between equations (4) and (8) is whether human capital enters the production function in levels or in logs. If human capital enters in logs - (4), there is a fixed human-capital elasticity in production for all countries. If it enters in levels - (8), human-capital elasticity in production will change across countries (and across time as well).

3 Econometric Estimation and Testing

Each one of these sets of equations in (4) and (8), conveniently reproduced below, constitutes a structural system of equations for a set of countries $i = 1, 2, \cdots N$ and a set of time periods $t = 1, 2, \cdots T$. As is usual with such a panel, panel-data techniques can be employed to estimate the structural parameters $\ln A_i$, α, β, g, and ϕ.

$$\begin{aligned} \ln y_{it} &= \ln A_i + \alpha \ln k_{it} + \beta \ln h_{it} + (1 - \alpha - \beta) g \cdot t + \eta_{it}; \\ i &= 1, 2, \cdots N \qquad t = 1, 2, \cdots T; \end{aligned} \tag{9}$$

$$\begin{aligned} \ln y_{it} &= \ln A_i + \alpha \ln k_{it} + (1 - \alpha)(\phi h_{it} + g \cdot t) + \eta_{it}; \\ i &= 1, 2, \cdots N \qquad t = 1, 2, \cdots T: \end{aligned} \tag{10}$$

If one disregards the panel-data structure in either (9) or (10), exploiting only the cross-sectional dimension of the data set, he/she cannot estimate either the technological-progress trend coefficient g, or the country-specific productivity level $\ln A_i$. Trying to do so would inevitably exhaust all available degrees-of-freedom. This is the main criticism of Islam (1995) of the estimation procedure in Mankiw, Romer and Weil (1992). Because we do not want to rule out a priori that $\ln A_i$ can be an important factor in explaining the observed disparity in output per worker across nations, we chose to consider the panel-data structure of the structural equations in (9) or (10).

In discussing the techniques to be employed in estimating either (9) or (10), the following have to be considered: (i) in general, $\ln k_{it}$ and $\ln h_{it}$ are correlated with η_{it}. This occurs for several reasons. In a short list, both $\ln k_{it}$ and $\ln h_{it}$ are measured with error, generating an error-in-variables problem in estimation; see Judge et al. (1985, pp. 706-709). Second, there is a portion of η_{it} that comes from productivity, hence being correlated with $\ln k_{it}$ and $\ln h_{it}$; (ii) because regressors and errors are correlated, if one hopes to get consistent estimates of structural parameters, a list of instrumental variables has to be obtained. These must be correlated with $\ln k_{it}$ and $\ln h_{it}$, but not with η_{it}; (iii) a choice must be made regarding how to model $\ln A_i$. There are two natural candidates: modelling $\ln A_i$ as a fixed-effect or as a random-effect.

Simultaneous-equation coefficients, such as the ones in either (9) or (10) above, can be consistently estimated by instrumental variable methods; see

Hsiao(1986, pp. 115-127). Considering the structure of correlation among errors of different countries is a first step in choosing the estimation method. A reasonable assumption about errors is that their variance is not identical across countries. Shocks to specific countries may be very different and may a cause for heteroskedasticity, which must then be considered in estimation. Errors for different countries should also have a non-zero contemporaneous correlation. There are several international shocks that simultaneously affect all countries: oil shocks, coordinated fiscal policies, etc. All potentially imply a contemporaneous correlation among errors. In the case of contemporaneous correlation, exploiting it leads to efficiency gains is estimation, i.e., more precise parameter estimates.

A textbook example of these relative efficiency gains is the comparison between 2SLS and 3SLS estimates. Precision, however, is not the only issue that should be considered in choosing the estimation method. Full-information methods (such as 3SLS) have also problems of their own, in which mis-specification of one given equation in the system carries over to other system equations, leading to inconsistent estimates for the whole system. Moreover, the larger the system, the higher the chance of mis-specification. Because in our case it may be preferable to have inefficient estimates (which can be consistent, in principle) than to have useless inconsistent estimates, we chose to use a method that does not take into account the contemporaneous correlation among errors. Heteroskedasticity of errors in different countries, however, will be considered in estimation. This is done by weighting differently every equation in the system.

The second step in instrumental-variable estimation is to obtain valid instruments. The discussion here is focused for the case of the (log of) the capital stock, but it generalizes for the case of the measure of human capital as well. When working with time-series data it is customary to consider the lags of the regressors as possible instruments for them, e.g., $\ln k_{t-1}$ as an instrument for $\ln k_t$. In the case of panel-data sets this is not a suitable choice. First, if the (log level of) capital is measured with a time-invariant error we have a typical error-in-variables problem; see Judge et al.(1985, pp. 706-709). In this case, $\ln k_{it-1}$ is correlated with ε_{it} because the latter includes the time-invariant measurement error present in the (log level of the) capital stock. Second, if ε_{it} contains a measurement error term for $\ln y_{it}$, and $\ln k_{it-1}$ is measured with error as well, with these two measurement errors being correlated, then $\ln k_{it-1}$ is again an unsuitable instrument.

To avoid the first problem discussed above, we consider as instruments not $\ln k_{it-1}$, but $\ln k_{jt-1}$, $i \neq j$, i.e., the lagged (log level of the) capital stock of country j. As long as the measurement errors are idiosyncratic in nature, i.e., uncorrelated with each other, $\ln k_{jt-1}$ will not be correlated with ε_{it}. A possible problem is that it may not be correlated with $\ln k_{it}$ either. For example, there is no guarantee that the lagged (log of the) capital stock of Fiji will be correlated with the current (log of the) capital stock in Romania. However, if we choose a group of countries j satisfying some geographical (or cultural) criterium, we can increase the chance of $\ln k_{jt-1}$ and $\ln k_{it}$ being correlated. In particular, we propose using for each country i the following instrument for $\ln k_{it}$:

$$\frac{1}{N^i}\sum_{j\in\{N^i\}} \ln k_{j,t-1}; \tag{11}$$

where N^i represents the number of additional countries in the same continent that country i is in, and $\{N^i\}$ represents the set of countries in that continent that are not country i, i.e., (11) represents rest-of-the-continent average lagged (log of the) capital stock.

Lagged average rest-of-continent capital stock looks promising as an instrument. Countries in the same continent usually trade more with each other than with countries outside that continent. They also tend to have similar macroeconomic policies. These factors contribute to deliver a non-zero correlation between $\frac{1}{N^i}\sum_{j\in\{N^i\}} \ln k_{j,t-1}$ and $\ln k_{it}$. On the other hand, one can argue that some component of $\frac{1}{N^i}\sum_{j\in\{N^i\}} \ln k_{j,t-1}$ may be correlated with ε_{it}. Although this is always possible, there is a way that the orthogonality between errors and instruments can be tested for over-identified models; basic references are Basmann (1960) and Sargan (1964).

Testing orthogonality for a specific over-identified regression equation in a system entails the following steps (see the discussion in Davidson and MacKinnon (1993, Section 7.8)):

1. Get the instrumental-variable residual for that equation. For example, for (9) above, get $\ln y_{it} - [\widehat{A_i} + \hat{\alpha}\ln k_{it} + \hat{\beta}\ln h_{it} + (1-\hat{\alpha}-\hat{\beta})\hat{g}\cdot t]$ for a given country in the sample, where hats denote instrumental-variable estimates.

2. Run an auxiliary regression of this instrumental-variable residual on the instruments used for that country, obtaining the uncentered R^2 statistic for the auxiliary regression.

3. Compute the $T \times R^2$ statistic, where T is number of observations used in estimation. $T \times R^2$ converges in distribution to a χ^2 statistic with $r-a$ degrees of freedom, where r and a are respectively the number instruments and the number of parameters in that particular equation, making $r-a$ the number of over-identifying restrictions for this particular equation.

4. Choose a significance level α and then compare $T \times R^2$ with $\chi^2_{r-a}(\alpha)$. Reject the null that the error and the instruments are orthogonal if $T \times R^2 > \chi^2_{r-a}(\alpha)$.

Although the procedure outlined above is suitable for testing "orthogonality" for single-equations in a system, it is a joint test of orthogonality and of correct specification of the model. Hence, rejection of the null can be due to incorrect specification and not to lack of orthogonality. However, it may be informative to compute this statistic in order to learn which countries violate either the orthogonality restrictions or correct specification. Similarities (or disparities) among them might shed light on what is the cause of the problem. Moreover, problem countries may be removed from the sample.

Whether or not human-capital measures should enter the production function in levels or in logs can be tested by using a Box and Cox(1964) transformation. Consider the generic regression equation:

$$y_t = \left(\frac{x_t^{\theta} - 1}{\theta}\right)\beta + \varepsilon_t. \tag{12}$$

Notice that

$$\lim_{\theta \to 0} \left(\frac{x_t^{\theta} - 1}{\theta}\right) = \ln(x_t); \text{ and} \tag{13}$$

$$\lim_{\theta \to 1} \left(\frac{x_t^{\theta} - 1}{\theta}\right) = x_t - 1; \tag{14}$$

where it is clear that for a logarithmic transformation to be valid we must have $\theta = 0$, and for a the series x_t to enter in levels we must have $\theta = 1$. These two hypotheses can be tested by means of a Wald test, using a Box-Cox transformation for the human-capital measure in the production function. Based on tests results we can then choose the more appropriate transformation for the human-capital series.

Finally, whether we should use fixed- or random-effects in modelling individual productivity factors $\ln A_i$ can be investigated by means of a Hausman(1978) test. The idea behind the test is very simple. Consider the generic regression:

$$y = X\beta + \varepsilon.$$

Suppose we want to test if the regressors X and the error ε are orthogonal, i.e., if $\text{plim}\frac{1}{n}X'\varepsilon = 0$, where n is the total number of observations available to estimate β. Consider now two possible estimators for β - $\hat{b}_0$ and $\hat{b}_1$. The latter is a consistent estimator for β regardless of whether $\text{plim}\frac{1}{n}X'\varepsilon = 0$. This is the estimate that uses fixed-effects, which is consistent in a variety of circumstances that the estimate using random-effects is not. On the other hand, $\hat{b}_0$ - the estimate that uses random-effects - is only consistent if $\text{plim}\frac{1}{n}X'\varepsilon = 0$, i.e., if the random effects contained in ε are not correlated with the regressors. If that is the case, it is also more efficient than $\hat{b}_1$. Assume that a usual Central-Limit Theorem applies for both estimators:

$$n^{1/2}\left(\hat{b}_0 - \beta\right) \xrightarrow{d} N(0; V_0); \text{ and}$$

$$n^{1/2}\left(\hat{b}_1 - \beta\right) \xrightarrow{d} N(0; V_1).$$

To test if $\text{plim}\frac{1}{n}X'\varepsilon = 0$, Hausman proposes a applying the following result (the difference between these two estimates):

$$n^{1/2}\left(\hat{b}_1 - \hat{b}_0\right) \xrightarrow{d} N\left[0; (V_1 - V_0)\right];$$

in the quadratic form:

$$n\left(\hat{\beta}_1 - \hat{\beta}_0\right)'(V_1 - V_0)^{-1}\left(\hat{\beta}_1 - \hat{\beta}_0\right) \xrightarrow{d} \chi^2_{\dim \beta}; \tag{15}$$

where $(V_1 - V_0)$ must be estimated consistently to have a feasible test statistic. If the difference between the two estimates is large, then (15) is large, and we are likely to reject the null. In this case, a large difference between estimators is taken to mean that $\text{plim}\frac{1}{n}X'\varepsilon \neq 0$, since otherwise we would expect this difference to be small (at least in large samples), because both estimates converge to the same vector of parameters β. An alternative application here would be to check whether or not OLS could be used to estimate production functions instead of instrumental-variable techniques. In this case, $\hat{\beta}_0$ will be the OLS estimator and $\hat{\beta}_1$ the instrumental-variable estimator.

4 Results

4.1 The Data

We considered two alternative panel data sets ranging from 1960 to 1985. The first uses observations at five-year intervals and the second uses annual data. Both combine macroeconomic data for 95 countries in the mark 5.6 of the Summers and Heston (SH, from now on) data set with human-capital measures contained in Barro and Lee (1996). Since the latter are only available at five-year intervals, our initial data set collected macroeconomic data with this frequency. However, this procedure is far from ideal, since production-function data will use non-contiguous observations and several years of data are left unused. Alternatively, we interpolated human-capital measures to fit annual frequency, thus inducing measurement error in human capital. This is, however, a minor problem, since human capital changes with a highly predictable pattern and the estimation technique used here allows for regressors that are measured with error. Most of the time, we report results for the annual data base, but occasionally we do as well for the five-year interval data set.

The time span was restricted from 1960 to 1985. Before the 1960's, macroeconomic data is missing for several developing countries, and using it would restrict too much the sample of countries. Limiting the final year to 1985 is required, since we wanted to include in our group of nations the previously socialist countries. Most of them made their transition into capitalism by the end of the 1980's, making 1985 the last possible year to include in the sample.

The specific series used are the following: y_{it} is the ratio of real GDP (at 1985 international prices) and the number of workers in the labor force, extracted from SH; k_{it} is the physical capital series per worker, which uses the real investment (at 1985 international prices) in constructing the capital series and the size of the labor force. Both are extracted from SH; h_{it} is Barro and Lee's (1996) series of average years of completed education of the labor force.

The way the physical-capital series were constructed deserves comment. We started with the investment series and applied the Perpetual Inventory Method to get measures os capital; see Young (1995, pp. 650-653) for a brief discussion. This method requires an initial capital level and a depreciation rate for physical capital. Since it is not obvious which is a reasonable depreciation rate to apply for all countries, we chose to use five different rates (3%, 6%, 9%, 12%, and 15%) checking whether the capital series were similar when they were permuted[1]. As for the initial capital stock, Young (1995, footnote 16) argues that it can be approximated by the following formula: $K_0 = I_0/(g_I + \delta)$, where K_0 is the initial capital stock, I_0 is the initial investment expenditure, g_I is the growth rate of investment, and δ is the depreciation rate of the capital stock. In computing his initial capital series, Young uses the mean growth of investment in the first five years of his sample as a proxy for g_I. In our case, since the early 1960's are a very unusual period in terms of the growth rate of all macroeconomic aggregates, in the sense of having relatively high growth rates for most countries, we chose to use the mean growth of investment from the whole sample (1960-85) in computing g_I.

4.2 Model Estimation

Instrumental-variable estimates of the mincerian model (10), using a limited-information setting for a variety of depreciation rates for the capital stock, are presented in Table 1. It also includes several test results - Box-Cox, Hausman, Sargan, etc. Instruments are country-specific, comprising $\frac{1}{N_i}\sum_{j \in \{N_i\}} \ln k_{j,t-1}$, $\frac{1}{N_i}\sum_{j \in \{N_i\}} h_{j,t-1}$, and t, and productivity ($\ln A_i$) is modelled as a fixed-effect. A Hausman (1978) test for choosing how to model $\ln A_i$ (random- versus fixed-effects) indicates that regressors are likely to be correlated with the random-effect, making the fixed-effects model the best alternative; see the p-values for the equality of coefficients in Table 1. The reported estimates for α, ϕ, and g do not change much as we vary depreciation rates. For reasonable values of δ (6%-12% interval), the estimate of α is about 0.41, the one for ϕ is about 0.08, the one for g is about 0.014; all are statistically significant at usual levels.

These numbers are close to what could be expected a priori: several calibrated studies use a capital elasticity $\alpha = 1/3$ (see Cooley and Prescott (1995) and McGrattan (1994)). Estimates in Gollin (1996) are also close to 0.40. As discussed above, ϕ can be interpreted as a measure of the percentage increase in income of an additional year of schooling. Mincerian regressions usually find $\hat{\phi} \simeq 0.10$ (Mincer (1974)). Moreover, Psacharopolos (1994) surveys schooling-return evidence using a large set of countries. He finds an average of 6.8% for OECD countries and 10.1% for the world as a whole. An average growth rate of productivity of about 1.4% a year is not unlikely, being in line with the evidence on long-run growth presented by Maddison (1995).

Instrumental-variable estimates of the extended neoclassical growth model (9) are presented in Table 2. Instruments are country-specific comprising $\frac{1}{N_i}\sum_{j \in \{N_i\}} \ln k_{j,t-1}$, $\frac{1}{N_i}\sum_{j \in \{N_i\}} \ln h_{j,t-1}$, and t. Due to the Hausman-test result, productivity ($\ln A_i$)

[1] Regression estimates for α and β did not change much when the depreciation rate varied. However, the estimate of g is sensitive to the choice of depreciation rate.

is modelled as a fixed-effect. For reasonable depreciation rates (6%-12% interval), the estimate of α is about 0.43, a little bit higher than in the mincerian case. The estimate of the growth rate of productivity g is about 1.9% a year, maybe closer to the conventional-wisdom than the mincerian estimate. Human-capital elasticity estimates $\hat{\beta}$ are relatively small: about 0.025 and, for some values of δ, not significantly different from zero.

A small and insignificant human-capital elasticity for the extended neoclassical model has also been reported by Benhabib and Spiegel (1994) and Klenow and Rodriguéz-Clare (1997)[2]. In light of this collective evidence, it may be interesting to understand why Mankiw Romer and Weil (1992) obtained such high estimates for human capital in the extended neoclassical model - ranging from 0.28 to 0.37[3]. Klenow and Rodriguez-Clare show that the results in Mankiw, Romer and Weil are not robust to changes in the proxies used to measure human capital. Moreover, Islam (1995) argues that productivity is likely to change across countries, which requires the use of panel data in estimation. Using cross-sectional data forcefully imposes the restriction that, apart from residual variation, productivity is the same for all countries.

Since productivity is correlated with physical and human capital, omitting it as a regressor could change dramatically elasticity estimates. To investigate this issue further, we re-estimated the extended neoclassical model under the restriction that productivity is the same across countries, i.e., that $\ln(A_i) = \ln(A)$, $\forall i$. The results, presented in Table 3, show an increment in the estimates of α and β. The first jumps from about 0.43 to about 0.60, while the second jumps from about 0.025 to about 0.12 - almost five times higher[4].

It seems that the key to understanding these differences in estimates lies in how to model productivity: if it is allowed to vary across countries as a fixed-effect, physical- and human-capital elasticities in production are relatively small. However, if it is restricted such that $\ln(A_i) = \ln(A)$, $\forall i$, estimates closer to Mankiw Romer and Weil's are produced. It turns out that we can choose between these to specifications using an econometric test: a Wald test for coefficient restrictions in the form $\ln(A_i) = \ln(A)$, $\forall i$. Results of these tests are presented in the last lines of either Tables 1 and 2 for the mincerian growth model and the extended neoclassical model respectively. For both models, and all values of δ, this restriction is overwhelmingly rejected, showing that the fixed-effect specification is appropriate, and that productivity indeed varies across countries.

As discussed above, we can choose which of the two models ((10) or (9)) best fits the data by using a Box-Cox test for the human-capital measure. Results are presented in either Tables 1 or 2. Numerically, the estimates of θ (not reported) were all very close to one and are very significant. Thus, testing that $\theta = 0$ - the double-log model in (9) - rejects the null for every value of the depreciation rate δ. On the other hand, testing that $\theta = 1$ - the log-level model in (10) -

[2] Klenow and Rodriguéz-Clare (1997) have also shown that using different human capital series delivers different estimates for β.

[3] See the results in their Table 2, p. 420.

[4] See also the results in Table 4 for the mincerian growth model.

does not reject the null for any value of δ. Hence, based on these test results, we prefer the mincerian specification over the extended neoclassical one. Since the basic difference between them is whether the human-capital elasticity is constant across countries (and time), our results indicate that this is probably too strong a restriction.

Because we want to check whether or not suitable instruments were used in estimating the structural models, we performed a series of Sargan tests (orthogonality between instruments and errors, equation-by-equation). The first step is to design an over-identified model, since the ones in Tables 1 and 2 are just-identified. We used three lags of our instrument list above, and t as well, in getting over-identified equations[5]. Since each equation estimates three coefficients, and we are using seven instruments, we should compare the test statistic with a χ^2_4. Results for the mincerian model are presented in Table 1. If we take the significance level to be 5%, from a total of 95 country-regressions, between 14 and 21 countries rejected the null in this "instrument-validity" test. This is about 16%-22% of the sample of countries, a relatively low number[6]. For the extended neoclassical model the results are not very different; see Table 2.

Although in terms of number countries these rejections are relatively small, since the data for each country are weighted by the variance of its error term in computing instrumental-variable estimates, it could happen that including these countries makes a big difference in terms of parameter estimates. To check if this was a potential problem, we ran mincerian regressions excluding from our sample of countries those for which we rejected orthogonality at the 5% level in the Sargan test. For all values of δ used, the results of this exercise showed overwhelmingly that estimates changed very little when these countries are excluded. To illustrate these differences, we report here the case of $\delta = 9\%$. For the restricted sample of countries, parameter estimates are the following: $\hat{\alpha} = 0.4127$, $\hat{\phi} = 0.0798$, and $\hat{g} = 0.0135$, whereas for the unrestricted sample they are: $\hat{\alpha} = 0.4196$, $\hat{\phi} = 0.0753$, and $\hat{g} = 0.0140$, i.e., virtually the same results.

It is useful at this point to summarize our evidence regarding production-function estimates using panel data. First, for both production functions considered, it is clear that productivity is better modelled as a fixed-effect vis-a-vis a random-effect. This happens because there is evidence from a Hausman (1978)

[5] Another concern in designing these tests was to avoid any additional functional form restrictions other than linearity. As explained above, this type of test is a joint test of specification and orthogonality. Any functional form restriction is tested together with orthogonality. Since we want to isolate orthogonality as much as possible, the only functional form restriction we impose is linearity. Hence, we did not impose the restrictions that coefficients are the same across countries, nor did we impose the homeogeneity restrictions that $\gamma = (1 - \alpha - \beta)$ for the extended neoclassical model or that $\beta = (1 - \alpha)$ for the mincerian model.

[6] When using the 9% depreciation capital stock, the 15 countries for which the instruments list is not valid are at 5% the following: Swaziland, Canada, Argentina, Colombia, Guyana, Peru, Venezuela, Israel, Jordan, Finland, the Netherlands, Portugal, Switzerland, Fiji, and Czechoslovakia. If we vary the depreciation rate used in constructing capital, this list changes very little. What is interesting is the relatively high number of South-American countries in the list, which may suggest that shocks to the region may be common to all countries and not idiosyncratic.

test that the random-effects are correlated with the regressors. Second, if we test whether or not productivity is the same across countries, i.e., that $\ln(A_i) = \ln(A)$, $\forall i$, regardless of the production function and the depreciation rate considered, the results show unequivocally that it is not. This raises suspicion that estimates that impose this type of restriction are biased and inconsistent; e.g., Mankiw, Romer and Weil (1992). Third, based on the evidence of the Box-Cox test, we chose the mincerian growth model over the extended neoclassical model. Hence in our preferred set of models, productivity is allowed to change across countries and human-capital enters the production function in level (not logs).

The next step is to get production-function estimates to investigate the nature of income inequality across nations. To do so, however, we first have to choose a depreciation rate. As the results of Table 1 show, it makes little difference in terms of parameter estimates which depreciation rate δ is used in constructing the physical-capital series. This is not surprising: a similar conclusion has been reached previously, among others, by Benhabib and Spiegel (1994). They chose to use 7% as a benchmark for δ. Here we decided to use 9% instead, although using almost any of the tabulated results would make little practical difference. The results of the mincerian growth model, reproduced below for annual data, and 9% depreciation rate, will be used as the benchmark in examining the nature of income inequality across nations.

Coefficient	α	ϕ	g
Estimate	0.420	0.075	0.014
(t-Statistic)	(71.92)	(12.05)	(24.60)

5 On The Nature of Output-per-worker Inequality

5.1 Productivity, Dynamic Distortions, and Variance Decomposition of output per worker

Table 5 reports the estimated (total factor) productivity - relative to the U.S. - of a selected group of countries; the full set is presented in the Appendix. Only six economies are more productive than the U.S. economy, five of which are oil producers. This result is not surprising, since our measure of capital does not include mineral and/or natural resources. Additionally, the following two findings are worth mentioning. First, all ex-communist countries are amongst the least productive economies. For example, Romania has the second smallest productivity, which is more than four times smaller than that of the U.S. Moreover, the U.S.S.R. and Czechoslovakia are respectively only 43% and 37% as productive as the U.S. These results are particularly striking: even after correcting for education and for the stock of physical capital, the average worker of Romania still produces four times less than the average American worker, and U.S.S.R.'s estimated productivity is the same as Ghana's. Second, the productivity levels of Japan, Taiwan, and Korea are below-average for world standards, which is consistent with Young's (1995) result that the good growth performance of some Asian countries in the recent past was mostly due to factor accumulation, not to productivity.

In general, productivity levels of the rich countries - particularly those in Europe - are above average. On the other hand, productivity of the poor countries are below average. Figure 1 depicts a cross-plot between productivity and the average output per worker, showing a positive relationship between them, with a correlation coefficient of about 0.50. For example, output per worker in the U.S. is 30 times larger than that in Niger and 22 times larger than that in Kenya, while the estimated productivity for these countries are respectively 34% and 28% of the U.S. productivity. On the other hand, GDP per-worker in Canada is 94% of that of the U.S., while its productivity is 92% of that of the U.S. Taken together, our estimates show that differences in productivity may be a candidate in explaining why output per worker varies so much across countries, a view opposite to that held by Chari, Kehoe and McGrattan (1997) and Mankiw, Romer and Weil (1992).

We next perform a naive variance-decomposition exercise (in a sense that will become clear shortly) in order to understand what are the fractions of the variance of output per worker explained either by inputs or by productivity. We take all variables measured at the last time period of our sample (1985) and disregard the uncertainty in parameter estimates. Thus, given $\widehat{\ln A_i}$, $\hat{\alpha}$, $\hat{\phi}$, and $\hat{g}$ and the structural model in 1985, with its error term ε_i replaced by its unconditional expectation (zero), we have:

$$\ln y_i = \ln A_i + \alpha \ln k_i + (1 - \alpha)(\phi h_i + g \cdot 1985): \qquad (16)$$

We decompose the variance of (the log of) output per worker in 1985 ($\ln y_i$) in terms of (the log of) productivity ($\ln A_i$), (the log of) capital per worker ($\ln k_i$), and (the level of) human-capital per-worker (h_i).

The variance of productivity, physical capital, and human capital account respectively for 21%, 49% and 2% of the variance of output per worker. The remaining 28% is accounted for by the covariances between these factors. The first thing to notice is that the estimate for the productivity contribution is a lower bound. This happens because we ignore the error term in performing the variance decomposition, but there is a portion of the variation of the error term ε_i which is correlated to productivity. Second, if we ignore the covariance terms (which usually are reallocated if one orthogonalizes these factors), we conclude that physical capital variation is by far the most important factor explaining output per worker variation.

The exercise just performed is naive because it does treat each factor as exogenous in calculating the variance decomposition. This is particularly troublesome for physical capital, since, for example, part of its variation may be induced by productivity variation under the exogenous productivity[7]. Indeed,

[7] This is ignored by Mankiw, Romer, and Weil (1992) when they use the R^2 statistic to measure the relative contribution of inputs for output variation. This happens despite the fact that their regression equation is based on the extended neoclassical model, in which the

for a given investment rate, an exogenous increase (decrease) in productivity will increase (decrease) the incentive to accumulate capital in the long run, increasing (decreasing) the capital per-worker ratio. Hence, part of the impact of physical capital on output is induced by productivity, and this is not taken into account in performing the exercise above.

In order to avoid that problem, Hall and Jones (1999) expressed the production function in terms of the capital-output ratio, not in terms of the capital-labor ratio. The way we chose to cope with this problem here was to call in more theory. We follow Chari, Kehoe and McGrattan (1997) in considering that capital accumulation is determined, on the one hand, by productivity, and, on the other hand, by the taxes on capital. Assuming that in 1985 (the last year in the sample) each economy had already reached its steady state path, and taking the modified golden rule from the one-sector model of optimum capital accumulation, it is possible to write[8]:

$$
\begin{aligned}
\alpha(1-\tau_i)A_i k_i^{\alpha-1} e^{(1-\alpha)\psi h_i} &= \rho+\delta+g; \\
\forall i &= 1,2,\cdots,N; \qquad (17)
\end{aligned}
$$

where ρ stands for the household's intertemporal discount rate, δ is the depreciation rate of physical capital, and τ_i is a purely intertemporal distortion, thus labelled as dynamic distortion. Since all countries grow at the same rate g in the long run, τ_i is the amount needed in each country to make the net return on capital equal to $\rho+\delta+g$. Ceteris paribus, the higher τ_i is, the smaller is the incentive for capital accumulation, and hence, the smaller is the capital per-worker ratio in the long run. This way the net return to capital is equated across economies. Note also that, if capital accumulation is due uniquely to productivity variation, then the τ_i that solves equation (17) will not be correlated with output.

Using equation (17), and calibrating $\rho = 0.99$, $\delta = 0.09$, and $g = 0.014$, we solve the system for τ_i. Figure 2 shows that there is a clear negative correlation between τ_i and output per worker. Moreover, as can inferred by looking at Figure 3, the correlation between τ_i and $\exp(\ln(A_i))$ is virtually zero (-0.03). Hence, some countries with relatively high productivity have no dynamic distortions, and vice-versa. For example, the U.S.S.R., which has a relatively low productivity, has the lowest value for the dynamic distortion τ_i; Romania, the second least productive country, has the fourth lowest value of τ_i; Japan, a country where productivity is below-average, has the third lowest τ_i. On the other hand, Iraq, the most productive country overall[9], is highly dynamically distorted - the 18th highest value of τ_i; countries such as Guatemala and Bangladesh, that had surprisingly high productivity, fared very poorly in terms of τ_i. Hence, economies that are very good at combining inputs not necessarily

only exogeneous factor is productivity, and, for which, it makes little sense to treat physical capital as exogeneous.

[8] We assume here that the intertemporal elasticity of substitution in consumption is unity for all countries.

[9] Probably due to oil reserves in its territory.

have the right incentives to boost capital accumulation, e.g., property rights or stable institutions. On the other hand, the ex-communist countries, and some Asian countries - Japan, Korea and Taiwan, that are relatively unproductive, have the right incentives or institutions to foster capital accumulation.

There are three possible reasons why the dynamic distortion measure τ_i is uncorrelated with productivity. First, it is possible for an economy to combine productively inputs without having the safeguards to guarantee property rights, or without having stable institutions. In that case, dynamic distortions will be high, although productivity is high. Second, for oil producers, our productivity estimate will be overestimated, since physical capital does not include mineral and/or natural resources, but that does not imply a low dynamic distortion. Finally, for strategic or political reasons, some countries have had policies favoring excessive capital accumulation, i.e., a low dynamic distortion. But this does not imply that they can combine inputs productively. The most striking examples are the former communist economies and the East Asian countries.

Including this new variable, τ_i, recognizes that physical capital is an endogenous variable in the overall system. In this case, we can solve (17) for k_i in terms of A_i, τ_i, and h_i, substituting the result into the production function:

$$y_i = \left(\frac{\alpha}{\rho+\delta+g}\right)^{\frac{\alpha}{1-\alpha}} A_i^{\frac{1}{1-\alpha}} (1-\tau_i)^{\frac{\alpha}{1-\alpha}} \exp(\phi h_i); \qquad (18)$$

or in logarithmic terms:

$$\begin{aligned} \ln y_i &= \ln\left[\left(\frac{\alpha}{\rho+\delta+g}\right)^{\frac{\alpha}{1-\alpha}}\right] + \frac{1}{1-\alpha}\ln(A_i) \\ &\quad + \frac{\alpha}{1-\alpha}\ln(1-\tau_i) + \phi h_i. \qquad (19) \end{aligned}$$

Using (19) we can now decompose the variance of $\ln y_i$ in terms of the variance of $\ln(A_i)$, $\ln(1-\tau_i)$, and h_i, recognizing that physical capital is an endogenous variable in the overall model. The results show that productivity alone explains 54% of $\ln y_i$ variance, human capital explains 5%, and the dynamic distortion component - the ultimate cause of physical capital differences - explains 21%. The remaining 20% are accounted for by covariances. These numbers are very different from those of the previous naive exercise, showing that, when the indirect effect of productivity on capital is considered, the importance of productivity jumps from 21% to 54% of output variance (disregarding covariance terms).

5.2 Classifying Countries according to Productivity, Dynamic Distortion, and Human-Capital Figures

Next, the sample of countries is divided according to their relative position (i.e., above or below average) for the three factors explaining (the log of) income per-worker: productivity, dynamic distortion, and human-capital. Hence, we divided these group of nations into $2^3 = 8$ groups, according to their relative position for each of these factors. The full classification of countries is shown in the Appendix, but Table 6 summarizes the results. The first group of countries - high productivity and human capital and low dynamic distortion - is composed almost exclusively of rich countries - essentially the OECD countries plus Hong-Kong and Singapore[10]. Their average income per-worker is twice as large as that of the second group. They are richer than the rest because they are more educated, very productive and have little distortions affecting capital accumulation. On the other hand, the group of nations that have the wrong incentives for long-run growth (unproductive, uneducated and dynamically distorted) is composed of 25 poor or very poor nations. Their average output per worker is a tenth of the average of the first group. Typical nations here are the Sub-Saharan countries, Pakistan, India, Haiti and Bolivia.

The group with the 2nd highest average income is composed of 13 nations with well educated labor force, relatively little dynamic distortions but below-average productivity. All the ex-communist countries, as well as Japan, Korea, and Taiwan, belong to it. The 3rd group is composed of 6 Latin American and Caribbean countries, such as Barbados, Uruguay and Chile. Those are well educated countries, relatively productive but the incentives for capital accumulation are poor.

The 4th group is composed of only four nations, Brazil, Portugal, South Africa and Algeria. These countries are relatively productive and have little dynamic distortions but the schooling level of their labor force is below average. The result for Brazil is expected: its good growth record in the 1970's was mostly based on physical-capital accumulation and above-average productivity. The latter can be explained by the abundance of natural resources and by its long tradition as a market economy. Contrasting to these favorable incentives to grow, the average years of education of the labor force was only 3.39 years in 1985[11], and there has been no serious governmental policy to improve these figures. It is interesting to have Portugal in the same group of Brazil, showing that the effects of a particular type of colonization may be long lasting. The 5th group has only one above-average factor (productivity), and it is composed mostly by oil producers and countries rich in other natural resources.

One interesting thing about this way of dividing nations is that the average income per-worker for groups declines monotonically with the number of factors hampering long-run growth; see Table 6. Hence, the long-term gains for a country to "fix" one hampering factor is always positive, and in some cases can be considerably high. For example, a country that jumps from the group with exactly one hampering factor, to the group of no hampering factor, will more than double (and maybe even triple) its long-run output per worker: Brazil would be twice as rich if its labor force was more educated; Argentina will be twice as rich if its distortions on capital accumulation were considerably smaller.

[10] The exception is Argentina. However, its estimated τ_i is almost equal to the average τ_i, only 0.02% smaller than it.

[11] Brazil is the the 41th richest country in our data set (in income per-worker terms) but ranks 70th in education attainment.

The main conclusion of this exercise is that there is no single factor explaining long-run growth. Hence, trying to find a single culprit for lack of growth can be a futile exercise: there may be a single factor for a given country, but not for the group of countries analyzed here. Examples are abundant, even within the same continent in some cases: Senegal and Zimbabwe had almost the same output per worker in 1985 - around 7% of the U.S. level. However, productivity in Senegal is 50% larger than that in Zimbabwe, while dynamic distortions in Senegal is 80% higher; New Zealand and Belgium had around 70% of U.S. output per worker in 1985, and about the same productivity. However, the average schooling of the labor force in New Zealand was 40% higher than that in Belgium, while its dynamic distortion was 24% higher. Of course, policy recommendations have to take country differences into account, or else they have a high chance of being ineffective.

5.3 Counter-Factual Exercises on Long-Run Growth

Table 7 displays a counter-factual exercise on long-run growth, which helps in understanding the nature of income inequality across nations. The second column displays 1985 output per worker (relative to the U.S.) - Y_i/Y_{US}. The third column shows relative income corrected for dynamic distortions, i.e., where country i is given the same distortion of the U.S. economy. The fourth column corrects for human capital and dynamic distortion, i.e., where country i is given the same distortion and human capital of the U.S. economy[12].

Most of the time relative output increases when we allow a country to have the U.S. dynamic distortion and human capital measures; see the case of Argentina, Mexico, and particularly for Mozambique, where output per worker increases by almost seven times. However, there are exceptions: for Japan and all other ex-communists countries, output decreases when we allow them to have the U.S. dynamic distortion[13]. Given that the education level observed in these countries is similar to the American level, the fourth column shows that if it was not for capital accumulation, income per capita in these countries would be almost half the actual difference. In other words, if Japan is allowed to have the same educational level and dynamic distortion of the U.S. its output per worker would be 0.38 of the U.S. level, not 0.70 times.

There are groups of countries, such as India and Niger, where the increase in relative income brought about by the reduction of dynamic distortions and improvement in education is not very large. In this case, most of the difference between them and the U.S. is due to productivity differences. European countries which have output per worker close to that of the U.S., such as the Netherlands, Austria, and France, would not change much too, but for different reasons: their τ_i; h_i and $\ln(A_i)$ are already very close to that of the U.S. econ-

[12] A different way to look at the fourth columm of Table 7 is to regard it as the relative output of a country, which is identical to the U.S. in everything, but productivity. See the Appendix for the entire set of countries.

[13] For the latter, it may be due to the implicit "subsidy" a comunist regime gives to capital accumulation.

omy. However, this pattern is not uniform across Europe: if Spain had the same incentives to capital accumulation and educational level than has the U.S., its relative output would have jumped from 45% to 73% of the latter.

An interesting case is that of Mexico. If it had the same ¿_i as the U.S., its output per worker would be twice as large as its is. Moreover, if it also had the same educational level as the U.S., its output per worker would be almost the same as that of the U.S. This is also observed in all oil-producer and some nature rich countries as their productivity is relatively large (and in 6 cases, larger than that of the U.S.).

It deserves note that even after correcting for factor di¤erences across countries, there still remains a large income disparity left unexplained. On average, output per worker of the 95 nations in our data set is 29% of that of the U.S. After substituting their ¿_i and h_i for the corresponding values of the American economy, the average output per worker increases to only 48% of the U.S. output, the rest corresponds to total factor productivity di¤erences.

Finally, we performed the following counterfactual exercise: for each country, we used output per worker in 1985 as a benchmark, replacing, one at a time, each of the factors explaining growth (productivity, human capital, and the dynamic distortion) by the respective U.S. factor. This allows measuring how much each of these factors contribute to the reduction in income disparity across nations. Figure 9 presents Kernel densities of the actual and counterfactual data. The factor that reduces the most the variance of output per worker is productivity. It drops from 0.97 in the actual data to 0.45 when productivity in every country is replaced by U.S. productivity. The dynamic distortion reduces the variance from 0.97 to 0.56, and human capital from 0.97 to 0.70.

One could ask why we did not follow Hall and Jones (1999) (among others) in basing our decomposition on the capital-output ratio. The problem with this procedure is that the capital-output ratio is very sensitive to recessions. Hence, some countries which have inherently a small capital-output ratio, would be considered capital intensive in recession years. The opposite would happen during booms[14]. Indeed, if we replicate the exercise of Table 6, following Hall and Jones, and using 1985 data, the group division delivers several counter-intuitive results[15]. First, countries such as Chile, Peru, and Uruguay would be classi…ed as capital-intensive therefore included in the group of rich countries. This happens because they were experiencing a recession in 1985. Second, while in Table 6 there is a clear income di¤erence among groups, depending of the number of factors hampering growth, this is no longer the case in this exercise. The group of rich countries would be, on average, only 13% richer than the group of well educated, productive, but dynamically distorted countries (contrasting to a di¤erence of more than 50% in our exercise). The variance decomposition exercise, however, using their method, reached results very similar to ours.

[14] On the other hand, ¿_i, which is calculated from (4), only depends on A_i, h_i and k_i. The …rst two are parameters of the production function, and the last is not too sensible to business cycle ‡uctuations.

[15] The whole set of results, using the method in Hall and Jones, is available upon request.

5.4 Simulations

A final question to be answered is how well the model chosen here fits the data. It is a well known result that the standard neoclassical model does not replicate well the observed path of post-war economies. In general, convergence is either too fast, or the implied interest rate at the initial periods is extremely high. Possible solutions to these problems included the use of additional stock variables or an increase in the capital share α.

The simulations of our model, for most economies, delivered artificial paths that replicate quite closely that of the actual data. Figures 4 through 8 below present the simulated and actual path, from 1960 to 1985, of the output per worker of 5 selected countries (Indonesia, Singapore, Ireland, Colombia, and Brazil). They illustrate the strengths and weaknesses of simulating equation (4) above - the "Mincerian Growth Model" - using the parameter estimates of our preferred regression (9% depreciation).

Figures 4 through 6 (and especially the first three) display quite a good match. For the case of the two Asian countries the model is able to replicate the transition path observed in the beginning of the sample period. Although productivity ($\ln(A_i)$) in the mincerian model only varies across countries (but not across time) we were able to replicate the high increase of output per worker in the transition path without having to resort to an increase in productivity. The same is true for other fast growing Asian countries such as Taiwan, Korea, and Malaysia. The model also replicates quite well the output path of Ireland and many other Europeans countries such as Norway, France, UK, Finland, etc.

There are two cases of mismatch between actual and simulated behavior for output per worker that illustrate the limitations of the model used here. For Colombia (Figure 7), it looks like the slope of the simulated path is a little bit smaller than the actual one. Indeed, it may be that for Colombia, the capital elasticity in production is different from "the world average" estimated in the panel regression. Our estimation procedure imposes the restriction that capital elasticities are the same across countries and across time (as is customary for panel estimates), but its use may be inappropriate for Colombia, causing the observed discrepancy between the simulated and the actual path of output per worker. The case of Brazil (Figure 8) is one where the hypothesis that $\ln(A_i)$ does not depend on time may be unreasonable. Between 1965 and 1968, Brazil experienced a radical program of economic and institutional reform. A new and less distorcive tax system was introduced and the financial system was modernized. The actual behavior of output per worker may be showing that there is a structural break in TFP after these reforms, whereas the simulated path is much smoother and its slope does not change at all in this period.

Although the Colombian and Brazilian cases are not the only ones where the model misbehaves, that did not happen very frequently. As a matter of fact, for the vast majority of simulations we observe results similar to those of Figures 4 through 6. Most of the exceptions are observed in the cases of countries that experienced a war or a revolution, so productivity decreases sharply during and after these episodes[16].

6 Conclusion

Understanding the nature of output per worker differences across countries should be one of the main objectives of the literature of economic growth, since the level of output per worker today can be thought as the cumulative growth experienced by a given country. Several authors have decomposed output per worker into the contribution of inputs and productivity, using different methodologies, and obtaining different results.

In this paper we used a different approach. First, we considered that estimating production-function parameters should be the starting point of this discussion. Because productivity can be different across countries, we used panel-data techniques in estimation, since their use allow for country-specific productivity levels. We also distinguish between two classes of production functions: the extended neoclassical growth model, and the mincerian growth model. The tests conducted here show that the mincerian growth model fits the data better than the extended neoclassical model. Moreover, econometric estimates and tests show that productivity varies considerably across countries: even after controlling for human and physical capital inputs, our estimates show that productivity differences as high as four still remains. Also, after endogenizing capital accumulation, the variation of productivity explains about half of the variation of output per worker. Thus, the conclusion that inputs alone can explain the variation of output per worker can be called into question.

Productivity, however, cannot explain all the variation of output per worker. There are groups of countries that are rich (1985), but their productivity is relatively low (e.g., Japan and Finland), or extremely low (U.S.S.R.). They are rich because of high levels of education and because they have high incentives for physical-capital accumulation. On the other hand, some countries where productivity was above average do not belong to the group of the rich nations, either because their labor force is uneducated (e.g. Brazil) or because the incentives for capital accumulation are not present (e.g. Uruguay and Argentina).

We showed that the gains for correcting the "factors that hamper growth" can be considerably high. The average income per capita of the group of nations with well educated labor force, little dynamic distortion, and high productivity is at least twice as high as that of any other group with exactly one factor hampering growth. The average income of the group of nations with all 3 factors below average is only one tenth of the group of rich nations.

The picture that emerges from this study is one where countries grew in the past for different reasons. Hence, a uniform policy applied to all nations is bound to be ineffective. Although there is not a single-factor explanation for the difference in output per worker across nations, it seems that productivity differences can explain a considerable portion of income inequality, followed

[16]For some Latin American countries such as Mexico, Uruguay, and Paraguay, the observed drop in output per-worker after the 1982 debt crisis is also not matched by the model.

second by dynamic distortion and third by human capital accumulation. The next challenge is to understand why some countries are so efficient in combining its inputs while others are not, and why some countries have the right incentives for capital accumulation while others have not.

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Parameters/Statistics	Depreciation Rates (±)				
	3%	6%	9%	12%	15%
®	0.4038	0.4124	0.4195	0.4183	0.4176
(t-ratio)	(66.58)	(70.62)	(71.92)	(73.80)	(75.00)
Á	0.0916	0.0870	0.0753	0.0772	0.0760
(t-ratio)	(13.69)	(13.64)	(12.05)	(12.93)	(13.24)
g	0.0140	0.0138	0.0140	0.0140	0.0142
(t-ratio)	(22.61)	(23.44)	(24.60)	(25.63)	(26.90)
Box-Cox µ = 1 (p-value)	0.7520	0.7153	0.7517	0.9112	0.7743
Box-Cox µ = 0 (p-value)	0.0000	0.0000	0.0000	0.0000	0.0000
Hausman: RE vs. FE (p-value)	0.0000	0.0000	0.0000	0.0000	0.0000
Sargan: Rejections at 5%	21/95	20/95	15/95	14/95	14/95
Wald test for no FE (p-value)	0.0000	0.0000	0.0000	0.0000	0.0000

Table 1: Estimates of the Mincerian Growth Model Log-Level Model

Parameters/Statistics	Depreciation Rates (±)				
	3%	6%	9%	12%	15%
®	0.4097	0.4217	0.4325	0.4287	0.4273
(t-ratio)	(68.77)	(72.95)	(74.60)	(75.59)	(76.09)
¯	0.0278	0.0320	0.0215	0.0256	0.0227
(t-ratio)	(2.20)	(2.61)	(1.76)	(2.11)	(1.87)
g	0.0204	0.0195	0.0187	0.0194	0.0197
(t-ratio)	(51.44)	(50.24)	(49.40)	(53.09)	(55.70)
Box-Cox µ = 1 (p-value)	0.7520	0.7153	0.7517	0.9112	0.7743
Box-Cox µ = 0 (p-value)	0.0000	0.0000	0.0000	0.0000	0.0000
Hausman: RE vs. FE (p-value)	0.0000	0.0000	0.0000	0.0000	0.0000
Sargan: Rejections at 5%	22/95	19/95	21/95	17/95	17/95
Wald test for no FE (p-value)	0.0000	0.0000	0.0000	0.0000	0.0000

Table 2: Estimates of the Extended Neoclassical Growth Model - Double-Log Model

Parameters/Statistics	Depreciation Rates (±)				
	3%	6%	9%	12%	15%
®	0.5154	0.5665	0.5931	0.5967	0.5979
(t-ratio)	(193.32)	(181.32)	(194.15)	(192.25)	(189.65)
Á	0.0654	0.0696	0.0565	0.0573	0.0587
(t-ratio)	(23.35)	(23.42)	(19.73)	(21.04)	(22.47)
g	0.0118	0.0071	0.0085	0.0101	0.0113
(t-ratio)	(18.83)	(10.99)	(12.83)	(15.08)	(16.82)
Wald test for no FE (p-value)	0.0000	0.0000	0.0000	0.0000	0.0000

Table 3: Estimates of the Mincerian Growth Model with no …xed E¤ects

Parameters/Statistics	Depreciation Rates (±)				
	3%	6%	9%	12%	15%
®	0.5143	0.5706	0.6023	0.6043	0.5982
(t-ratio)	(187.52)	(174.29)	(171.73)	(171.71)	(166.51)
¯	0.1901	0.1583	0.1098	0.1208	0.1314
(t-ratio)	(27.59)	(22.40)	(15.22)	(17.07)	(18.54)
g	0.0185	0.0120	0.0112	0.0139	0.0169
(t-ratio)	(18.58)	(11.80)	(11.62)	(14.00)	(16.55)
Wald test for no FE (p-value)	0.0000	0.0000	0.0000	0.0000	0.0000

Table 4: Estimates of the Extended Neoclassical Growth Model with no Fixed Effects

Country	Relative Productivity
Iran	1.23
Netherlands	0.93
Canada	0.92
Spain	0.88
Argentina	0.81
Brazil	0.71
Chile	0.67
Japan	0.58
Korea	0.56
Indonesia	0.44
U.S.S.R.	0.43
Ghana	0.43
India	0.36
Kenya	0.29
Romania	0.23
Malawi	0.20

Table 5: Relative Productivity Estimate for Selected Countries (U.S.= 1.00)

Table 6

Group	Features	Countries	"Bad" Features	Mean Income
1	Productive, Non-distorcive and Educated	23	0	11280
2	Unproductive, Non-distorcive and Educated	13	1	5379
3	Productive, Distorcive and Educated	6	1	5343
4	Productive, Non-distorcive and Uneducated	4	1	3849
5	Productive, Distorcive and Uneducated	16	2	2793
6	Unproductive, Distorcive and Educated	3	2	2289
7	Unproductive, Non-distorcive and Uneducated	5	2	1934
8	Unproductive, Distorcive and Uneducated	25	3	1130

Table 6: Country Classification According to Different Factors

Country	$Y_i = Y_{US}$ (Uncorrected)	$Y_i = Y_{US}$ (¿$_i$ = ¿$_{US}$)	$Y_i = Y_{US}$ ($h_i = h_{US}$; and ¿$_i$ = ¿$_{US}$)
Argentina	0.32	0.53	0.64
Brazil	0.24	0.34	0.48
Mozambique	0.05	0.34	0.55
Niger	0.03	0.08	0.13
India	0.06	0.10	0.15
Japan	0.71	0.33	0.38
U.S.S.R.	0.42	0.21	0.23
Spain	0.45	0.58	0.73
Netherlands	0.71	0.73	0.83
Mexico	0.34	0.71	0.93

Table 7: Relative Output of Selected Countries in Counter-Factual Analysis

Country	Y/L	A	¿	h
USA	1.00	1.00	1.00	1.00
Canada	0.94	0.92	0.79	0.87
Switzerland	0.90	0.89	0.30	0.79
Norway	0.85	0.81	0.09	0.66
Australia	0.82	0.79	0.35	0.89
Sweden	0.81	0.83	0.66	0.82
Denmark	0.78	0.70	0.45	0.90
Germany West	0.76	0.81	0.26	0.74
Iceland	0.74	0.77	0.39	0.67
France	0.74	0.82	0.29	0.55
Finland	0.73	0.62	-0.41	0.80
Japan	0.71	0.58	-0.11	0.76
Netherlands	0.70	0.93	0.68	0.73
New Zealand	0.69	0.80	0.72	1.03
Belgium	0.68	0.85	0.58	0.74
U.K.	0.68	0.88	1.07	0.74
Austria	0.67	0.85	0.47	0.60
Italy	0.65	0.84	0.17	0.53
Hong Kong	0.64	0.69	1.15	0.73
Trinidad&Tobago	0.59	1.32	1.60	0.60
Singapore	0.52	0.72	0.25	0.53
Israel	0.50	0.73	0.69	0.81
Spain	0.45	0.88	0.70	0.54
Ireland	0.44	0.73	0.54	0.67
USSR	0.43	0.43	-0.64	0.83
Cyprus	0.39	0.56	0.44	0.62
Venezuela	0.38	1.23	1.44	0.49
Greece	0.38	0.66	0.58	0.63
Barbados	0.37	0.79	1.58	0.65
Mexico	0.34	1.03	1.44	0.45
Taiwan	0.33	0.60	0.97	0.66
Argentina	0.32	0.81	1.18	0.61
Yugoslavia	0.31	0.53	0.08	0.59
Portugal	0.31	0.67	0.74	0.34
Iraq	0.26	1.71	1.87	0.30
Syria	0.26	1.04	1.49	0.38
Mauritius	0.26	0.66	1.79	0.47
Korea Rep.	0.25	0.56	1.02	0.75
Malaysia	0.25	0.64	0.90	0.48
Iran	0.24	1.23	1.61	0.28
Brazil	0.24	0.71	1.13	0.29
Uruguay	0.24	0.75	1.38	0.60

Table 8: Relative position of countries (U.S. = 1.00)

Country	Y =L	A	¿	h
Czechoslovakia	0.24	0.37	0.21	0.80
Jordan	0.21	0.93	1.47	0.45
Panama	0.21	0.61	1.13	0.57
Chile	0.21	0.67	1.24	0.56
South Africa	0.20	0.69	1.19	0.45
Fiji	0.20	0.65	1.29	0.65
Costa Rica	0.19	0.78	1.56	0.47
Reunion	0.19	0.55	1.12	0.35
Algeria	0.18	0.78	0.85	0.28
Colombia	0.18	0.69	1.41	0.40
Ecuador	0.18	0.58	0.90	0.51
Tunisia	0.17	0.74	1.61	0.29
Peru	0.15	0.67	1.35	0.52
Thailand	0.15	0.44	1.40	0.45
Botswana	0.14	0.49	1.15	0.29
Jamaica	0.13	0.44	0.90	0.38
Swaziland	0.13	0.68	1.76	0.35
Dominican Rep.	0.13	0.73	1.60	0.35
Guatemala	0.13	0.89	1.95	0.24
Paraguay	0.13	0.67	1.65	0.43
Sri Lanka	0.12	0.64	1.95	0.50
Romania	0.12	0.23	0.05	0.68
El Salvador	0.11	0.76	1.99	0.29
Nicaragua	0.11	0.80	1.83	0.30
Bolivia	0.11	0.46	1.21	0.41
Indonesia	0.10	0.44	1.35	0.35
Papua N.Guinea	0.10	0.49	1.49	0.17
Philippines	0.09	0.48	1.48	0.58
Cameroon	0.09	0.55	1.97	0.24
Honduras	0.08	0.56	1.71	0.35
Guyana	0.08	0.39	0.63	0.47
Pakistan	0.08	0.54	1.88	0.19
Bangladesh	0.07	0.76	2.33	0.18
Zimbabwe	0.07	0.35	1.20	0.23
Senegal	0.07	0.52	2.21	0.19
India	0.06	0.36	1.55	0.32
Lesotho	0.06	0.42	1.88	0.30
Nepal	0.06	0.62	2.24	0.11
Haiti	0.05	0.61	2.25	0.25
Liberia	0.05	0.35	1.68	0.19
Zambia	0.05	0.27	0.76	0.38
Kenya	0.05	0.29	1.41	0.29

Country	Y =L	A	¿	h
Ghana	0.05	0.43	2.11	0.31
Mozambique	0.05	0.79	2.52	0.07
Togo	0.04	0.30	1.49	0.24
Central Afr.R.	0.04	0.35	2.13	0.13
Myanmar	0.04	0.30	1.94	0.21
Niger	0.03	0.34	1.98	0.06
Uganda	0.03	0.57	2.46	0.13
Mali	0.03	0.46	2.21	0.07
Malawi	0.03	0.20	1.39	0.24
Tanzania	0.03	0.25	1.85	0.23
Zaire	0.03	0.55	2.39	0.22

Country	Y=L	corrected by ¿	corrected by h
USA	1.00	1.00	1.00
Canada	0.94	0.79	0.85
Switzerland	0.90	0.71	0.79
Norway	0.85	0.55	0.65
Australia	0.82	0.62	0.65
Sweden	0.81	0.64	0.70
Denmark	0.78	0.51	0.53
Germany West	0.76	0.58	0.66
Iceland	0.74	0.50	0.60
France	0.74	0.52	0.65
Finland	0.73	0.52	0.65
Japan	0.71	0.33	0.38
Netherlands	0.70	0.73	0.83
New Zealand	0.69	0.69	0.68
Belgium	0.68	0.63	0.72
U.K.	0.68	0.66	0.75
Austria	0.67	0.57	0.69
Italy	0.65	0.53	0.67
Hong Kong	0.64	0.43	0.49
Trinidad&Tobago	0.59	1.21	1.47
Singapore	0.52	0.41	0.52
Israel	0.50	0.50	0.55
Spain	0.45	0.58	0.73
Ireland	0.44	0.46	0.55
U.S.S.R.	0.43	0.21	0.23
Cyprus	0.39	0.28	0.34
Venezuela	0.38	0.99	1.29
Greece	0.38	0.38	0.46
Barbados	0.37	0.51	0.61
Mexico	0.34	0.71	0.93
Taiwan	0.33	0.33	0.39
Argentina	0.32	0.53	0.64
Yugoslavia	0.31	0.25	0.30
Portugal	0.31	0.31	0.43
Iraq	0.26	1.53	2.17
Syria	0.26	0.69	0.93
Mauritius	0.26	0.33	0.43
Korea Rep	0.25	0.30	0.34
Malaysia	0.25	0.32	0.41
Iran	0.24	0.85	1.22
Brazil	0.24	0.34	0.48
Uruguay	0.24	0.46	0.56
Czechoslovakia	0.24	0.15	1.17

Table 9: Relative position of countries (U.S. = 1.00)

		corrected by	
Country	Y =L	¿	h
Jordan	0.21	0.59	0.78
Panama	0.21	0.31	0.39
Chile	0.21	0.36	0.45
South Africa	0.20	0.36	0.47
Fiji	0.20	0.37	0.44
Costa Rica	0.19	0.45	0.59
Reunion	0.19	0.23	0.31
Algeria	0.18	0.39	0.56
Colombia	0.18	0.34	0.46
Ecuador	0.18	0.27	0.35
Tunisia	0.17	0.36	0.52
Peru	0.15	0.36	0.46
Thailand	0.15	0.16	0.22
Botswana	0.14	0.18	0.26
Jamaica	0.13	0.16	0.22
Swaziland	0.13	0.32	0.45
Dominican Rep	0.13	0.37	0.51
Guatemala	0.13	0.48	0.70
Paraguay	0.13	0.33	0.44
Sri Lanka	0.12	0.32	0.42
Romania	0.12	0.06	0.07
El Salvador	0.11	0.37	0.53
Nicaragua	0.11	0.41	0.60
Bolivia	0.11	0.17	0.23
Indonesia	0.10	0.15	0.21
Papua N. Guinea	0.10	0.16	0.25
Philippines	0.09	0.21	0.26
Cameroon	0.09	0.20	0.30
Honduras	0.08	0.23	0.32
Guyana	0.08	0.14	0.18
Pakistan	0.08	0.20	0.29
Zimbabwe	0.07	0.09	0.14
Bangladesh	0.07	0.35	0.52
Senegal	0.07	0.18	0.38
India	0.06	0.10	0.14
Lesotho	0.06	0.13	0.19
Nepal	0.06	0.23	0.36
Haiti	0.05	0.25	0.36
Zambia	0.05	0.07	0.09
Kenya	0.05	0.07	0.10
Ghana	0.05	0.14	0.20
Mozambique	0.05	0.34	0.55
Togo	0.04	0.07	0.11

		corrected by	
Country	Y/L	¿	h
Central Afr.Republic	0.04	0.09	1.14
Myanmar	0.04	0.07	0.10
Niger	0.03	0.08	0.13
Uganda	0.03	0.20	0.32
Mali	0.03	0.14	0.22
Malawi	0.03	0.03	0.05
Tanzania	0.03	0.05	0.08
Zaire	0.03	0.21	0.30

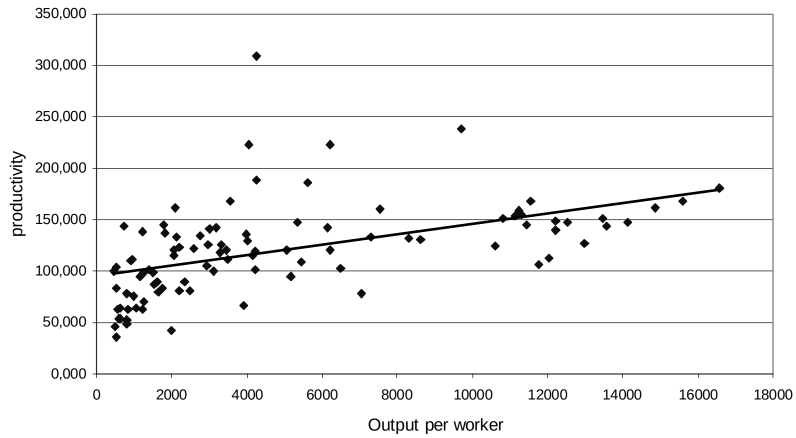

Figure 1: Estimated productivity and output per worker

Figure 2: Dynamic inefficiency and output per worker

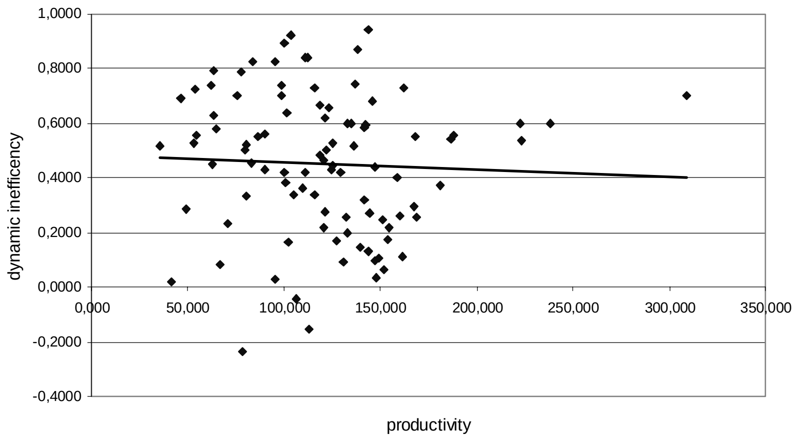

Figure 3: Dynamic inefficiency and estimated productivity

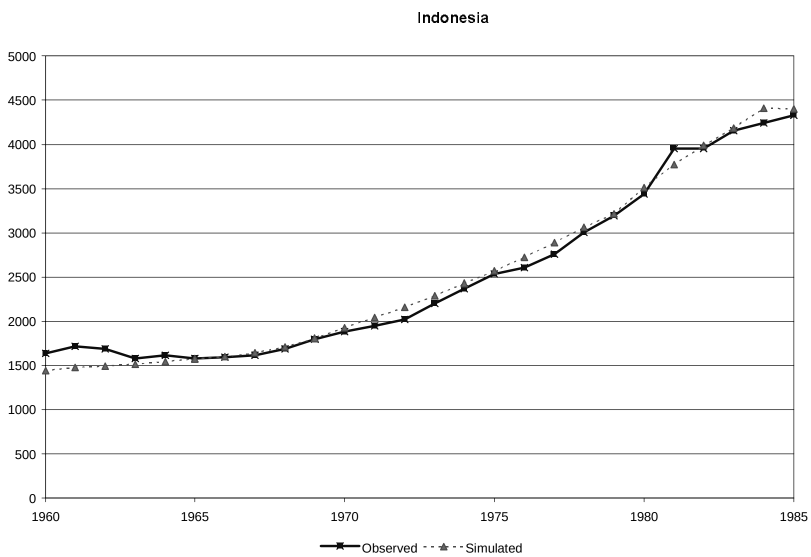

Figure 4: Observed and simulated output per worker (Indonesia)

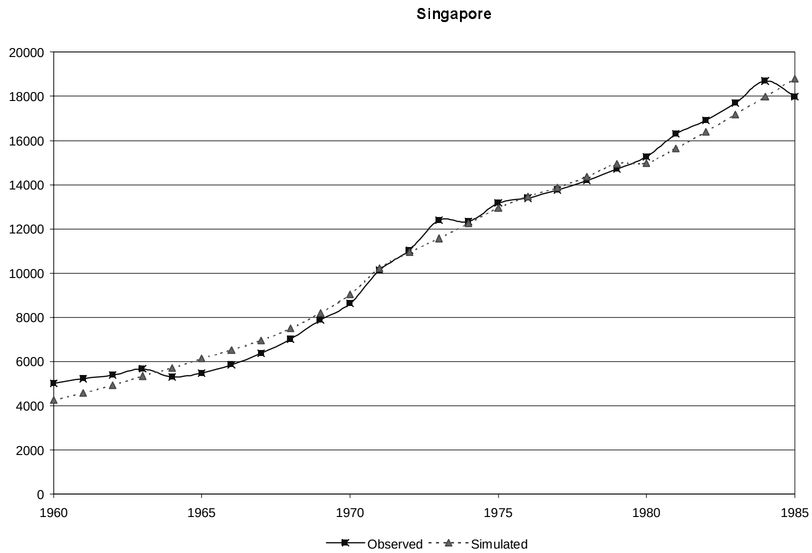

Figure 5: Observed and simulated output per worker (Singapure)

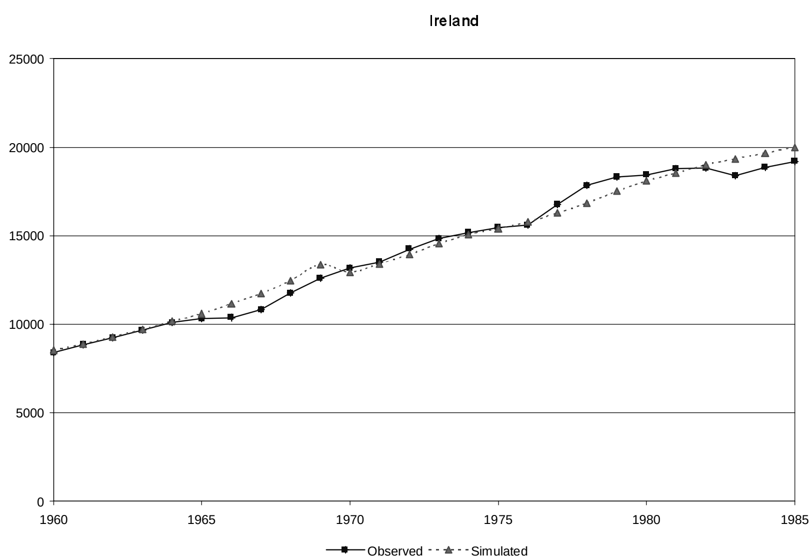

Figure 6: Observed and simulated output per worker (Ireland)

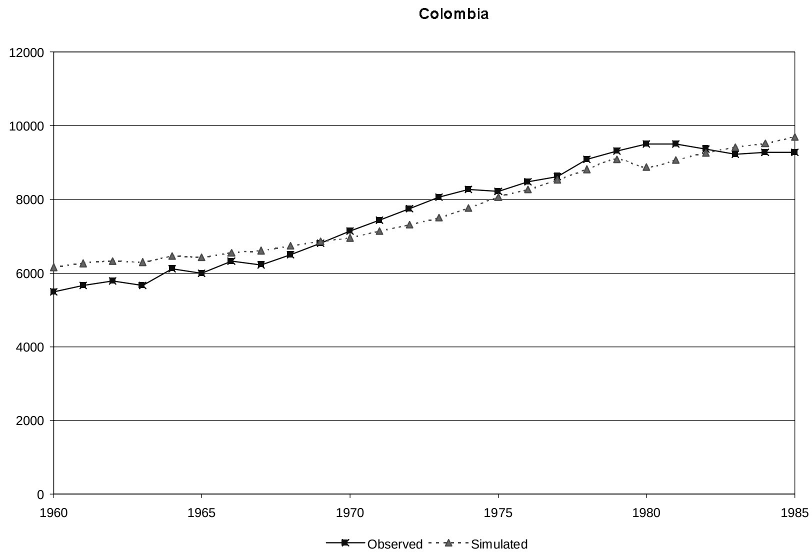

Figure 7: Observed and simulated output per worker (Colombia)

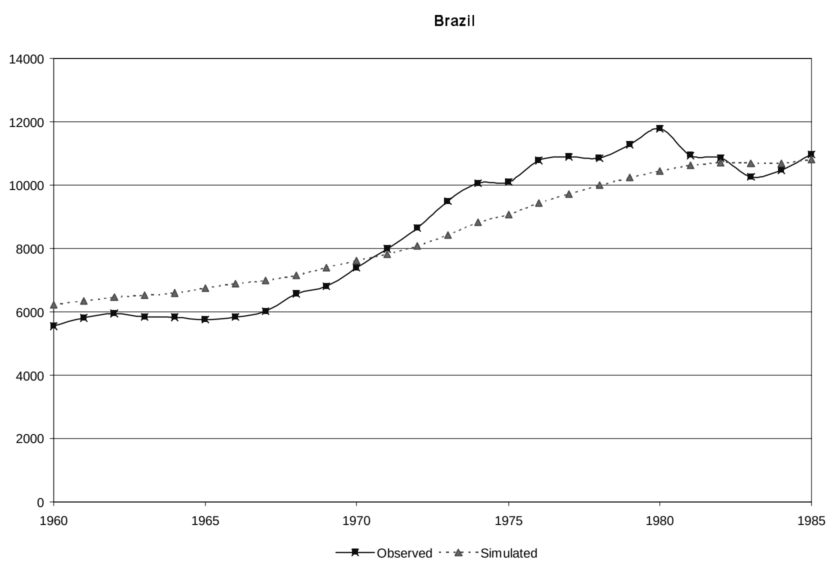

Figure 8: Observed and simulated output per worker (Brazil)

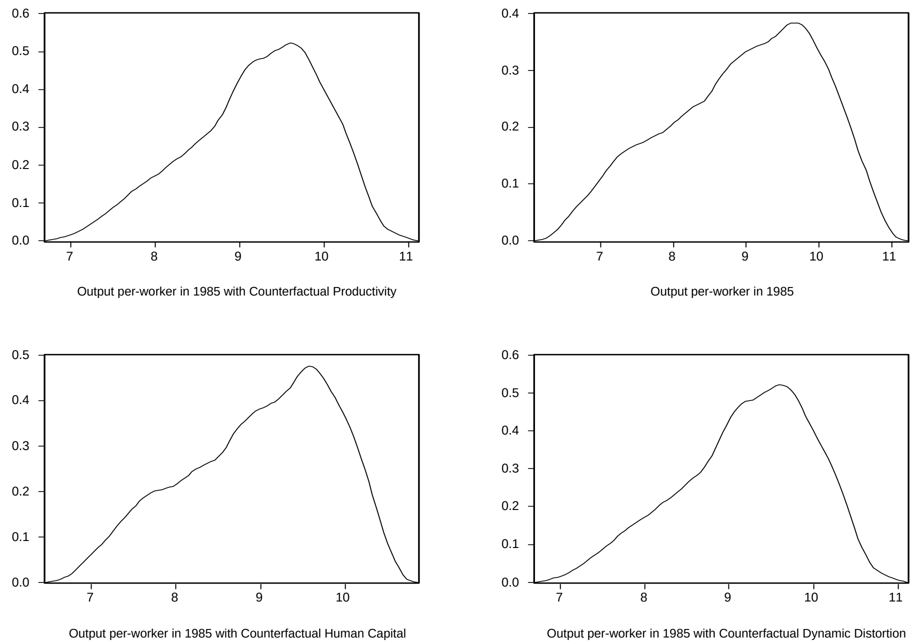

Figure 9: Kernel Densities of Counterfactual Output per-worker in 1985

Group 1: Productive, Non-distorcive and Educated

Canada, U.S.A., Argentina, Hong Kong, Israel, Singapore, Austria, Belgium, Denmark, France, Germany West, Greece, Iceland, Ireland, Italy, Netherlands, Norway, Spain, Sweden, Switzerland, U.K., Australia, New Zealand

Group 2: Unproductive, Non-distorcive and Educated

Panama, Ecuador, Guyana, Japan, Korea Rep., Malaysia, Taiwan, Cyprus, Finland, Yugoslavia, Czechoslovakia, Romania, U.S.S.R.

Group 3: Productive, Distorcive and Educated

Barbados, Trinidad&Tobago, Chile, Peru, Uruguay, Venezuela

Group 4: Productive, Non-distorcive and Uneducated

Algeria, South Africa, Brazil, Portugal

Group 5: Productive, Distorcive and Uneducated

Mozambique, Swaziland, Tunisia, Costa Rica, Dominican Rep., El Salvador, Guatemala, Mexico, Nicaragua, Colombia, Paraguay, Bangladesh, Iran, Iraq, Jordan, Syria

Group 6 Unproductive, Distorcive and Educated

Philippines, Sri Lanka, Fiji

Group 7: Unproductive, Non-distorcive and Uneducated

Botswana, Zambia, Zimbabwe, Jamaica, Reunion

Group 8: Unproductive, Distorcive and Uneducated

Cameroon, Central Afr. Republic, Ghana, Kenya, Lesotho, Liberia, Malawi, Mali, Mauritius, Niger, Senegal, Tanzania, Togo, Uganda, Zaire, Haiti, Honduras, Bolivia, Myanmar, India, Indonesia, Nepal, Pakistan, Thailand, Papua N.Guinea