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. First, rather than imposing functional forms or parameter values in calibration exercises that can potentially drive results, we first estimate, test, and distinguish between types of aggregate production functions currently used in the growth literature. Next, given our panel-regression estimates, we perform several exercises, such as variance decompositions, simulations and counter-factual analyses. The picture that emerges is one where countries grew in the past for different reasons, which should be an important ingredient in policy design. Although there is not a single-factor explanation for the difference in output per-worker across nations, productivity differences can explain a considerable portion of income inequality, followed by distortions to capital accumulation and then by human capital accumulation.

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1 Introduction

Recently, a number of studies in the fields of development and economic growth have focused on differences in the level of output per worker among countries rather than in differences of growth rates. For a given country, since the level of output per worker can be thought of as its cumulative growth experience, studying worker output can serve as a proxy for studying long-term growth.

Differences of output per worker across countries are indeed very high. For example, in 1990 the average worker in the U.S. produced 34 times more than a worker in Mali, 12 times more than one in Guyana or India, and twice as much as one in Portugal. Studies that have tried to explain these differences 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 an important factor in explaining the differences of output per worker 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 strengthened. On the other hand, Hall and Jones work with a production function where human capital is not a separate input, but modifies raw labor. Hence, there are only two factors, and not three: physical capital and labor. Moreover, they calibrate the physical-capital share to be relatively small (equal to 1/3). This type of specification automatically reinforces the role of productivity.

Since these methodological choices can potentially drive the final results obtained, one way of 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, and specific parameter values in calibration exercises, 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 them, we ask which of these two functional forms 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, taken 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.

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 vary considerably across countries, and testing whether productivity is the same for all countries strongly rejects this hypothesis. A variance decomposition exercise shows that productivity and dynamic distortion are the most important factors in explaining the variation in output per worker across countries: while productivity explains 53%, the dynamic distortions on capital accumulation explain 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. In 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 that of the rich-country group.

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 that in Brazil. This shows that these countries should pursue different development policies to reduce the gap between them and the group of rich nations. On the other hand, Japan, Taiwan, and South Korea, despite being low-distortion and high-education countries, have productivity levels that are below-average for world standards: South Korea's estimated TFP is only 56% 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 to high productivity.

Taken together, our evidence 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. Some countries are poorer, despite being relatively productive, because they impose strong restrictions on capital accumulation.

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 and the estimation results are presented. Section 4 is on the nature of income inequality across nations, and Section 5 concludes.

2 Model Specification

The first production function considered here is the so-called "extended neoclassical growth model," which uses human capital as an additional explanation for output, jointly with physical capital and raw labor. Start with the following homogenous-of-degree-one production function:

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

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:

$$\frac{Y_{it}}{L_{it}} = y_{it} = A_{it} F\left(k_{it}, h_{it}, \exp\left(g \cdot t\right)\right). \tag{2}$$

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

$$\ln y_{it} = \ln A_{it} + \alpha \ln k_{it} + \beta \ln h_{it} + \gamma g \cdot t + \varepsilon_{it}, \tag{3}$$

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:

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

where in the last line of (4) 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 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. There is only one type of labor in the economy, which has skill-level λ, 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:

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

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

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

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

$$\ln y_{it} = \ln A_{it} + \alpha \ln k_{it} + \beta \ln\left(\lambda_{it} \exp\left(g \cdot t\right)\right) + \varepsilon_{it}, \tag{7}$$

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

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

where, again, in the last line of (8) 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.

Econometrically, 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, Testing, and Results

3.1 Estimation and Testing

Each one of these sets of equations in (4) and (8) 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.

If one disregards the panel-data structure in either (4) or (8), exploiting only the cross-sectional dimension of the data set, one 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 (4) or (8).

In considering the techniques to be employed in estimating either (4) or (8), the following have to be taken into account: (i) in general, $\ln k_{it}$, $\ln h_{it}$, and h_{it} are correlated with η_{it}. This occurs for several reasons. In a short list, $\ln k_{it}$, $\ln h_{it}$, and 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 $\ln k_{it}$, $\ln h_{it}$, and 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 $\ln k_{it}$, $\ln h_{it}$, and 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 in the panel-data literature: modelling $\ln A_i$ as a fixed-effect or as a random-effect.

Simultaneous-equation coefficients, such as the ones in either (4) or (8) 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 be a cause for heteroskedasticity, which must then be considered in estimation. Errors for different countries should also have a non-zero contemporaneous correlation, because of common international shocks that simultaneously affect all countries. Exploiting it leads to efficiency gains in estimation, i.e., more precise parameter estimates.

Precision, however, is not the only issue that should be considered in choosing the estimation method. Full-information methods (such as full information maximum likelihood or 3SLS) also have 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 try to achieve these potential efficiency gains, running the risk of having 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 every equation in the system differently, using the reciprocals of the standard deviations of the country-specific errors as weights.

The second step in instrumental-variable estimation is to obtain valid instruments. We discuss here the case of the (log of) the capital stock, but a similar argument applies for the measures of human capital as well ($\ln h_{it}$ or h_{it}). Consider first as an intrument for $\ln k_{it}$, $\ln k_{jt-1}$, $i \neq j$, i.e., the lagged (log level of the) capital stock of country j[1]. Even if the capital stock is measured with error, creating an error-in-variable problem, 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 η_{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 of Romania. However, if we choose a group of countries j satisfying some geographical (or cultural) criterion, 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 $\ln k_{it}$:

$$\frac{1}{N^i} \sum_{j \in \{N^i\}} \ln k_{jt-1}, \tag{9}$$

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., (9) 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 $\frac{1}{N^i} \sum_{j \in \{N^i\}} \ln k_{jt-1}$ and $\ln k_{it}$. On the other hand, one can argue that some component of $\frac{1}{N^i} \sum_{j \in \{N^i\}} \ln k_{jt-1}$ may be correlated with η_{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 requires first using instrumental-variable residuals in running auxiliary regressions, and second constructing a $T \times R^2$ statisctic with the output

[1] We chose the lagged capital stock for country j to reduce further the chance of correlation between error and instrument.

of this auxiliary regression. Although the procedure 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. This requires avoiding imposing any restrictions on panel-regression estimates when testing for orthogonality.

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:

$$y_t = \left(\frac{x_t^\theta - 1}{\theta} \right) \beta + \varepsilon_t. \tag{10}$$

Notice that:

$$\lim_{\theta \to 0} \left(\frac{x_t^\theta - 1}{\theta} \right) = \ln(x_t), \text{ and} \tag{11}$$

$$\lim_{\theta \to 1} \left(\frac{x_t^\theta - 1}{\theta} \right) = x_t - 1, \tag{12}$$

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 the regression 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.

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. Estimates using fixed and random effects are compared by searching for departures of the latter from the former, which happens when the random component is correlated with regressors. A large difference is a sign of a non-zero correlation, which violates consistency for the parameters of the random effect model.

3.2 The Data

The panel data set used ranges from 1960 to 1985, and combines 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 extracted from Barro and Lee(1996). Since the latter are only available at five-year intervals, we first considered using a database with that frequency. However, this presents a problem, since production-function data will use non-contiguous observations and several years of data would be left unused. Alternatively, we decided to interpolate human-capital measures to fit annual frequency. Although this induces measurement error in human capital, the problem is relatively small, since human capital changes with a highly predictable pattern and the estimation technique used allows for regressors that are measured with error[2].

The time span was restricted from 1960 to 1985. Before the 1960's, and after 1985, macroeconomic data is missing for several developing countries. Limiting the final year to 1985 also has the advantage of including in our sample the previously socialist countries. Most of them made their transition into capitalism at 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. In the numerator it uses real investment data from SH (at 1985 international prices) in constructing the capital series; h_{it} is Barro and Lee's(1996) series of average years of completed education of the labor force, interpolated (in levels) to fit annual frequency.

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 of capital. 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 across depreciation rates. As for the initial capital stock, we followed Young(1995) and Hall and Jones(1999) and approximated it by $K_0 = I_0 / (g_I + \delta)$, 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. Here, since the early 1960's was 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

[2]To check the robustness of estimation results, we compared those using data with five-year intervals and those using yearly data. They were very close indeed.

mean growth of investment from the whole sample (1960-85) in computing g_I.

3.3 Model Estimation Results

Instrumental-variable estimates of the mincerian model (8), 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 $\frac{1}{N^i}\sum_{j\in\{N^i\}} \ln k_{jt-1}$, $\frac{1}{N^i}\sum_{j\in\{N^i\}} h_{jt-1}$, 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 (projected on instruments) 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, of ϕ about 0.08, and of g about 0.014; all are statistically significant at the 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(1997) are also close to 0.40 for a variety of countries. 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 $\widehat{\phi} \simeq 0.10$ (Mincer(1974)). Moreover, Psacharopolos(1994), who surveys schooling-return evidence using a large set of countries, 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 (4) are presented in Table 2. The same country-specific instruments were used. Due to the Hausman-test result, productivity ($\ln A_i$) 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 $\widehat{\beta}$ 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 Rodrigućz-Clare(1997). In light of this collective evidence, it may be interesting to understand why Mankiw Romer and Weil(1992) obtained high estimates for human capital elasticity 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 properly modelling country-specific productivity, since 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 considerably change 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; see also the results in Table 4 for the mincerian growth model.

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 an appropriate model for productivity 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 ((8) or (4)) 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,

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

testing that $\theta = 0$ - the double-log model in (4) - rejects the null for every value of the depreciation rate δ. On the other hand, testing that $\theta = 1$ - the log-level model in (8) - 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[4]. 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[5]. 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 were excluded. To illustrate these differences, we

[4]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 homogeneity restrictions that $\gamma = (1 - \alpha - \beta)$ for the extended neoclassical model or that $\beta = (1 - \alpha)$ for the mincerian model.

[5]When using the 9% depreciation rate of capital stock, the 15 countries for which the instruments list is not valid (at 5%) are 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.

report here the case of $\delta = 9\%$. For the restricted sample of countries, parameter estimates are the following: $\widehat{\alpha} = 0.4127$, $\widehat{\phi} = 0.0798$, and $\widehat{g} = 0.0135$, whereas for the unrestricted sample they are: $\widehat{\alpha} = 0.4196$, $\widehat{\phi} = 0.0753$, and $\widehat{g} = 0.0140$, 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) 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; e.g., Mankiw, Romer and Weil(1992), and that calibration exercises based on this assumption (e.g., those in Chari, Kehoe and McGrattan) can be misleading. 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 levels, 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, with 9% depreciation rate, will be used as the benchmark in examining the nature of income inequality across nations; $\widehat{\alpha} = 0.420$, $\widehat{\phi} = 0.075$, and $\widehat{g} = 0.014$.

4 On The Nature of Output-per-worker Inequality

4.1 Variance Decomposition of Output per Worker

To understand the relative contribution of inputs and productivity to the variance of output per-worker, three variance-decomposition exercises were performed. In all cases we take 1985 variables and disregard the uncertainty in parameter estimates. The first exercise is a naive-decomposition exercise (in a sense that will become clear shortly), the second endogeneizes capital accumulation, and the third follows Hall and Jones, among others, rewriting the per-worker production function in terms of the capital-output ratio.

In the "naive" decomposition, given the structural model in 1985 with its error term η_i replaced by its unconditional expectation (zero), we have:

$$\ln y_i = \ln A_i + \alpha \ln k_i + (1-\alpha)(\phi h_i + g \cdot 1985). \tag{13}$$

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).

This exercise is naive because it treats 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. Indeed, for a given investment rate, an exogenous increase in productivity will increase the incentive to accumulate capital in the long run, raising 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

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 using the modified golden rule, we have[6]:

$$\begin{aligned} \alpha(1-\tau_i)A_i k_i^{\alpha-1}\exp\left[(1-\alpha)\phi h_i\right] &= \rho+\delta+g, \\ \forall i &= 1,2,\cdots,N, \end{aligned} \tag{14}$$

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 a dynamic distortion (to capital accumulation). We set $\delta = 0.09$, and $g = 0.014$ and $\rho = 0.026$ and solved (14) for τ_i. Since all countries grow at the same rate g in the long run, τ_i is the amount needed in each country to equalize the net return on capital across economies to $\rho+\delta+g$[7]. *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. In other words, it is postulated here that there is no (negative) relationship between capital per worker and returns, as in the standard neoclassical model, because τ_i equates returns across economies.

Including τ_i in the analysis recognizes that physical capital is an endogenous variable in the overall system[8]. In this case, we can solve (14) for k_i in terms of A_i, τ_i, and h_i. Substituting the result into the production function and taking logs, we have:

$$\begin{aligned} \ln y_i &= \ln\left[\left(\frac{\alpha}{\rho+\delta+g}\right)^{\frac{\alpha}{1-\alpha}}\right] + \frac{1}{1-\alpha}\ln(A_i) \\ &\quad + \frac{\alpha}{1-\alpha}\ln(1-\tau_i) + \phi h_i. \end{aligned} \tag{15}$$

Using (15) we can decompose the variance of $\ln y_i$ in terms of the variance of $\ln(A_i)$, $\ln(1-\tau_i)$, and h_i.

[6] We assume here that the intertemporal elasticity of substitution in consumption is unity for all countries; see the results in Hansen and Singleton(1982) for the U.S. using aggregate data.

[7] Hence, we assume that the net rate of return of capital is 4% for all countries.

[8] Human capital H_i is kept exogenous for three reasons. First, in all exercises its importance in explaining output variance is very small. Hence, making it endogenous would not affect the final results of the variance-decomposition exercise. Second, the importance of institutional factors such as family tradition and public school system are relatively important, maybe more than market forces. Finally, there is no obvious way of writing the transition equation for human capital, due among other reasons to spillover effects.

In the third decomposition, following Hall and Jones, the production function is rewritten as:

$$\frac{Y_i}{L_i} = A_i \frac{H_i}{L_i} \left(\frac{K_i}{Y_i} \right)^{\alpha/(1-\alpha)}, \tag{16}$$

where, in their case, $H_i = L_i \exp(\phi h_i)$. Taking logs of (16):

$$\ln y_i = \ln A_i + \phi h_i + \frac{\alpha}{1-\alpha} \ln \left(\frac{K_i}{Y_i} \right). \tag{17}$$

This formulation allows us to decompose the differences in output per-worker into differences in productivity, differences in human capital and differences in the capital-output ratio. Moreover, the effect of productivity on capital cancels out.

Comparing the three exercises, we think the second is the most appropriate overall. Compared to the first, it implicitly recognizes that physical capital is endogenous, a theoretical implication of the exogenous-growth model. It is better than the third for two reasons. First, a decomposition based on the capital-output ratio is too sensitive to recessions and booms. For instance, some countries which have inherently small capital-output ratios would be considered capital intensive in recession years. The opposite would happen during booms[9]. Second, using the dynamic distortion is interesting in its own right. Although it has been used before by Chari, Kehoe and McGrattan, one rarely sees in the growth literature accounting exercises in terms of distortions.

Table 5 presents the results of the variance-decomposition exercises. In the "naive" decomposition, 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. One 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 η_i which is correlated with productivity.

[9] On the other hand, τ_i, which is calculated from (4), only depends on A_i, h_i and k_i. The first two are parameters of the production function, and the last is not too sensible to business-cycle fluctuations. Indeed, some countries which we found to be highly distorcive, such as Peru and Uruguay, were found to be capital-intensive using the alternative methodology because they were experiencing a recession in 1985.

With all caveats in mind, physical capital variation can be an important factor explaining output-per-worker variation.

Results change considerably once physical capital is treated as an endogenous variable. The second line of Table 5 shows that productivity alone explains 54% of the variance of $\ln y_i$. Human capital explains 5%, and the dynamic distortion component - the ultimate cause of physical capital differences - explains 21%. These numbers are very different from those of the previous exercise, showing that when the indirect effect of productivity on capital is accounted for, it explains not one-fifth but one-half of the variance of $\ln y_i$[10]. The last row of Table 5 presents the results of the same variance-decomposition exercise when we restricted the number of countries to include only the 5 richest and 5 poorest in our sample. Productivity differences are still the main reason for income dispersion across countries.

Turning to the variance decomposition based on equation (17), we used as parameters values $\alpha = 0.42$, $\phi = 0.075$, and our estimates of $\ln A_i$. The results show that $\ln A_i$ and $\ln (K/Y)_i$ explain each exactly 45% of the variance of $\ln y_i$. Although the portion of the variance of $\ln y_i$ explained by factors has now increased, the importance of productivity cannot be denied.

One interesting thing about variance-decomposition exercises of this sort is that the results are sensitive to the capital share used. If we use $\alpha = 2/3$ - the same capital share used by Chari, Kehoe and McGrattan - a result close to theirs is obtained: factors alone explained 82% of output-per-worker variance. On the other hand, when the same capital share as in Hall and Jones is used ($\alpha = 1/3$), results are similar to theirs, with productivity explaining 61% of output variance. These differences in outcomes reinforce our initial point that the most reasonable approach for doing a growth-accounting exercise is to start with estimation and specification testing of a production function, instead of assuming *a priori* a given specification, later doing a calibration-exercise and a growth-accounting exercise based on it.

4.2 Productivity and Dynamic Distortions

Table 6 reports the estimated (total factor) productivity - relative to the U.S. - of a selected group of countries. Only six economies are more productive than the U.S. economy, five of which are oil producers. This result is not

[10] The model, calculated using equation (4), accounts for 82% of the dispersion of per worker income across countries in 1985.

surprising, since our measure of capital does not include mineral and/or natural resources.

Additionally, the following 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 similar to the ones in Hall and Jones: 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. Also, the U.S.S.R.'s estimated productivity is the same as Ghana's. Second, the productivity levels of Japan, Taiwan, and South Korea are below-average for world standards, owing to a relatively small 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 is below average. Figure 1 shows a cross-plot between productivity and output per worker in 1985. It displays 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 is 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.

It is illustrative, at this point, to examine the behavior of τ_i. Figure 2 shows that there is a clear negative correlation between τ_i and output per worker in 1985: rich nations distort capital accumulation less than poor nations do. Moreover, as can inferred by looking at Figure 3, the correlation between τ_i and A_i is virtually zero (-0.03). Hence, economies that are very good at combining inputs (i.e., are highly productive) do not necessarily have the right incentives to boost capital accumulation. On the other hand, the ex-communist countries, and some Asian countries that are relatively unproductive (Japan, Korea, and Taiwan), have incentives or institutions that foster capital accumulation: Japan's productivity is below world average but its dynamic distortion is the third lowest amongst all nations. These findings are 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.

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.

4.3 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 $\ln(A_i)$, the dynamic distortion τ_i, and human-capital h_i. Hence, we divided these sub-groups of nations into $2^3 = 8$ groups, according to their relative position for each of these factors. Table 7 summarizes the results; see Table 8 for the complete list of countries in each group. 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[11]. 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 few 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 1/10 of the average of the first group. Typical nations are the Sub-Saharan countries, Pakistan, India, Haiti and Bolivia.

The second group is composed of 13 nations with well educated labor forces, relatively few dynamic distortions but below-average productivity. All the ex-communist countries, as well as Japan, Korea, and Taiwan, belong to it. The third group is composed of six Latin American and Caribbean

[11]The exception is Argentina. However, its estimated τ_i is almost equal to the world average, being only 0.02% smaller.

countries, such as Barbados, Uruguay and Chile. Those are well educated countries, which are relatively productive, but have few incentives for capital accumulation.

The fourth group is composed of only four nations, Brazil, Portugal, South Africa and Algeria. These countries are relatively productive and have few 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 an 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 its labor force was only 3.39 years in 1985[12], and there has been no serious governmental policy to improve these figures. It is interesting to have Portugal in the same group as Brazil, showing that the effects of a particular type of colonization may be long lasting. The fifth group has only one above-average factor (productivity), and it is composed mostly of oil producers and of countries that are rich in other natural resources.

One interesting characteristic of this way of dividing nations is that the average income per worker for groups declines monotonically with the number of "bad" features (factors hampering long-run growth); see Table 7. Hence, the long-term gain for a country to "fix" one bad feature is always positive, and in some cases it can be considerably high. For example, a country that jumps from the group with exactly one bad feature to the group with no bad features will more than double (and maybe even triple) its long-run output per worker: Brazil would be twice as rich if its labor force were more educated; Argentina would be twice as rich if its distortions on capital accumulation were considerably smaller.

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% higher than that in Zimbabwe, while dynamic distortions in Senegal are 80% higher; New Zealand

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

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 either wrong or ineffective.

4.4 Counter-Factual Exercises on Long-Run Growth

Table 9 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 as 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 as the U.S. economy[13].

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 Mozambique, where output per worker increases by almost ten times. However, there are exceptions: for Japan and the ex-communist countries, output decreases when we allow them to have the U.S. dynamic distortion[14]. Given that the education level observed in these countries is similar to the American level, the fourth column shows that if it were not for capital accumulation, output per worker in these countries would be almost half of the actual difference.

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 either, but for different reasons: their τ_i, h_i and $\ln(A_i)$ are already very close to those of the U.S. economy. However, this pattern is not uniform across Europe: if

[13] A different way to look at the fourth column of Table 9 is to regard it as the relative output of a country, which is identical to the U.S. in everything but productivity. A Table with the entire set of countries is available upon request.

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

Spain had the same incentives to capital accumulation and educational level as the U.S., its relative output would have jumped from 45% to 73% of the latter's.

An interesting case is that of Mexico. If it had the same τ_i as the U.S., its output per worker would be twice as large as it 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 for all oil-producing countries and for countries rich in natural resources, since their productivity levels are relatively large (and in six cases, larger than that of the U.S.).

It deserves note that even after correcting for factor differences 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 τ_i and h_i with 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 differences.

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 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. The factor that reduces the variance of output per-worker the most is productivity. Output variance drops from 0.97 in the actual data to 0.45 when productivity in every country is replaced by U.S. productivity. Dynamic distortion reduces the variance from 0.97 to 0.56, and human capital from 0.97 to 0.70.

4.5 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 during the initial periods is extremely high; see King and Rebelo(1993). Possible solutions to these problems in the literature include 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 those 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. 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 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 in the mincerian model only varies across countries (but not across time), this does not seem to be a problem. The other two figures illustrate two types of mismatches between actual and simulated behavior. For Hong Kong (Figure 7), most of the time the slope of the simulated path is smaller than the actual one. Our estimation procedure imposes the restriction that capital elasticities are the same across countries and across time (as is customary for panel estimates), but this may be inappropriate for Hong Kong. The case of Brazil (Figure 8) is one where the hypothesis that $\ln(A_i)$ is time invariant may be unreasonable. Indeed, the actual behavior of output per worker may be showing that there was a structural break in TFP between 1965 and 1968. Although the Hong Kong and Brazilian cases are not the only ones where the model misbehaves, in the vast majority of simulations we observed results similar to those in Figures 4 through 6.

The model also fares relatively well on the simulations of rates of return. The initial level of rates of return to physical capital (actually, marginal products) implied by the transitional dynamics of the model remain within reasonable bounds for most countries: in 1960 it was 8% for Hong Kong and the Philippines, 19% for Japan, 16% for Thailand and 7% for Brazil. For India it was already close to the (calibrated) steady state rate of return of 1985 (4%). On the other hand, the initial rate of return of most rich countries was smaller than 6% in 1960. These differences are reasonable given expropriation risks, financial repression, and obstacles to capital mobility in LDC's at this time. There are, however, exceptions: the initial rate of return of Korea and Botswana was 42% and 65% respectively. For these two nations, it maybe that the hypothesis that τ_i is constant across time is inappropriate, as higher 1960 distortions would correct that problem.

5 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 of a given country can be thought of as its cumulative growth experience. Several authors have decomposed output per worker into the contribution of inputs and productivity, using different methods, and obtaining different results.

In this paper we recognize that different methodological choices in constructing a growth-accounting exercises can lead to very different results. Hence, we propose estimating and testing the specification of two types of production functions as a starting point for this exercise. Because productivity can be different across countries, we used panel-regression techniques in estimation, allowing for country-specific productivity levels. The two classes of production functions considered are: the extended neoclassical growth model and the mincerian growth model. The tests conducted here show that the latter fits the data better than the former. 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 remain. 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 rich nations: either because their labor force is under-educated (e.g. Brazil), or because the incentives for capital accumulation are relatively low (e.g. Uruguay and Argentina) or both (e.g., Mexico and Jordan).

We show that the gains for correcting the "factors that hamper growth" can be considerably high. The average output per worker 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. Moreover, the average income of the group of nations with all three factors below average is 1/10 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 likely to be either wrong or 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 second by the dynamic distortion in capital accumulation and third by human capital accumulation. The next challenge is to understand why some countries are so efficient in combining inputs while others are not, and why some countries have the right incentives for capital accumulation while others do not.

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A Econometric Testing

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 (4) above, get $\ln y_{it} - \left(\widehat{\ln A_i} + \widehat{\alpha} \ln k_{it} + \widehat{\beta} \ln h_{it} + (1 - \widehat{\alpha} - \widehat{\beta})\widehat{g} \cdot t\right)$ 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. This requires avoiding imposing any restriction on panel-regression estimates when testing for orthogonality.

To test whether to 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 straightforward. Consider the generic regression:

$$y = X\boldsymbol{\beta} + \varepsilon.$$

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 $\boldsymbol{\beta}$. Consider now two possible estimators for $\boldsymbol{\beta}$ - $\widehat{\boldsymbol{\beta}}_0$ and $\widehat{\boldsymbol{\beta}}_1$. The latter is a consistent estimator for $\boldsymbol{\beta}$ 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 where the estimate using random effects is not. On the other hand, $\widehat{\boldsymbol{\beta}}_0$ - 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 $\widehat{\boldsymbol{\beta}}_1$. Assume that a usual Central-Limit Theorem applies for both estimators:

$$n^{1/2}\left(\widehat{\boldsymbol{\beta}}_0 - \boldsymbol{\beta}\right) \xrightarrow{d} N\left(\mathbf{0}, \mathbf{V}_0\right), \text{and}$$
$$n^{1/2}\left(\widehat{\boldsymbol{\beta}}_1 - \boldsymbol{\beta}\right) \xrightarrow{d} N\left(\mathbf{0}, \mathbf{V}_1\right).$$

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

$$n^{1/2}\left(\widehat{\boldsymbol{\beta}}_1 - \widehat{\boldsymbol{\beta}}_0\right) \xrightarrow{d} N\left[\mathbf{0}, \left(\mathbf{V}_1 - \mathbf{V}_0\right)\right],$$

in the quadratic form:

$$n\left(\widehat{\boldsymbol{\beta}}_1 - \widehat{\boldsymbol{\beta}}_0\right)'\left(\mathbf{V}_1 - \mathbf{V}_0\right)^{-1}\left(\widehat{\boldsymbol{\beta}}_1 - \widehat{\boldsymbol{\beta}}_0\right) \xrightarrow{d} \chi^2_{\dim \boldsymbol{\beta}}, \tag{18}$$

where $(\mathbf{V}_1 - \mathbf{V}_0)$ must be estimated consistently to have a feasible test statistic. If the difference between the two estimates is large, then (18) 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 expect this difference to be small (at least in large samples) because both estimates converge to the same vector of parameters $\boldsymbol{\beta}$. 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, $\widehat{\boldsymbol{\beta}}_0$ would be the OLS estimator and $\widehat{\boldsymbol{\beta}}_1$ the instrumental-variable estimator.

B Figures and Tables

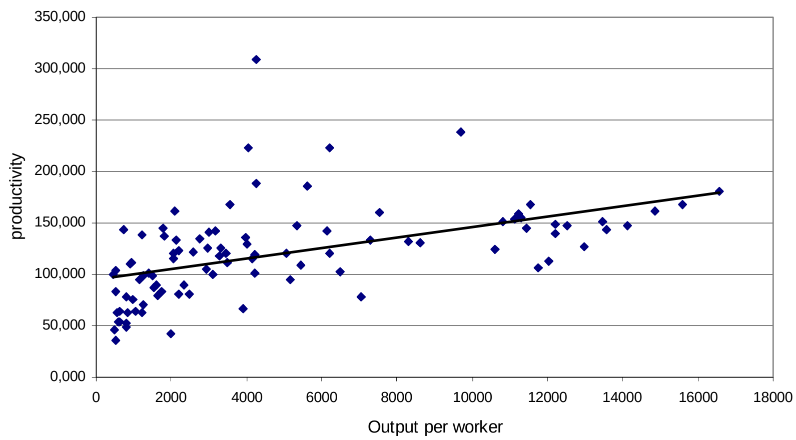

Figure 1: Estimated productivity and output per worker in 1985

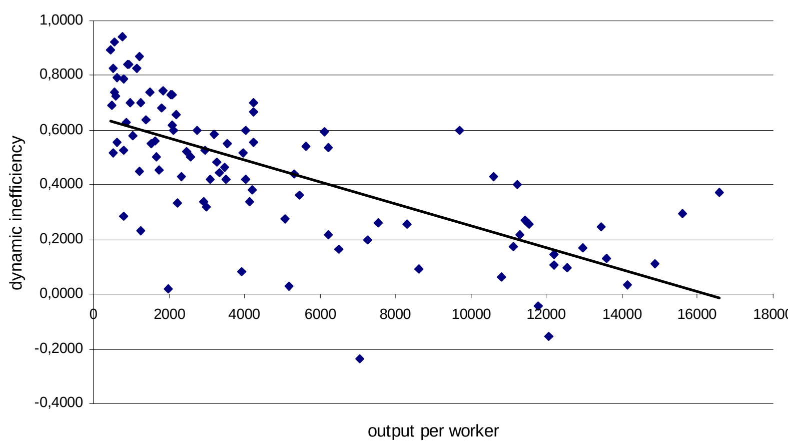

Figure 2: Dynamic inefficiency and output per worker in 1985

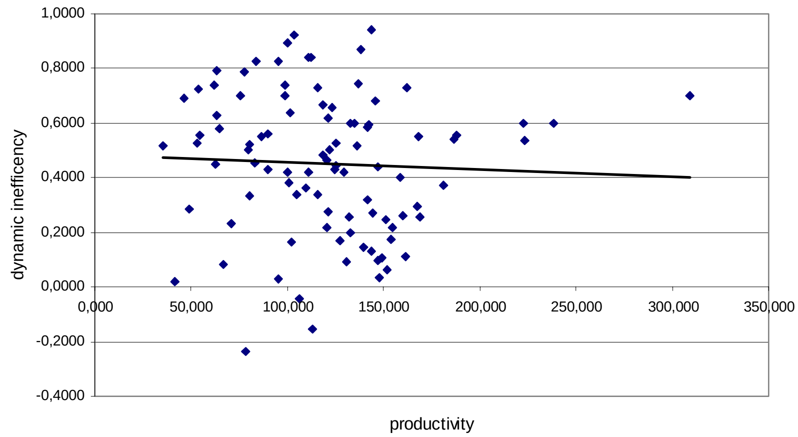

Figure 3: Dynamic inefficiency and productivity

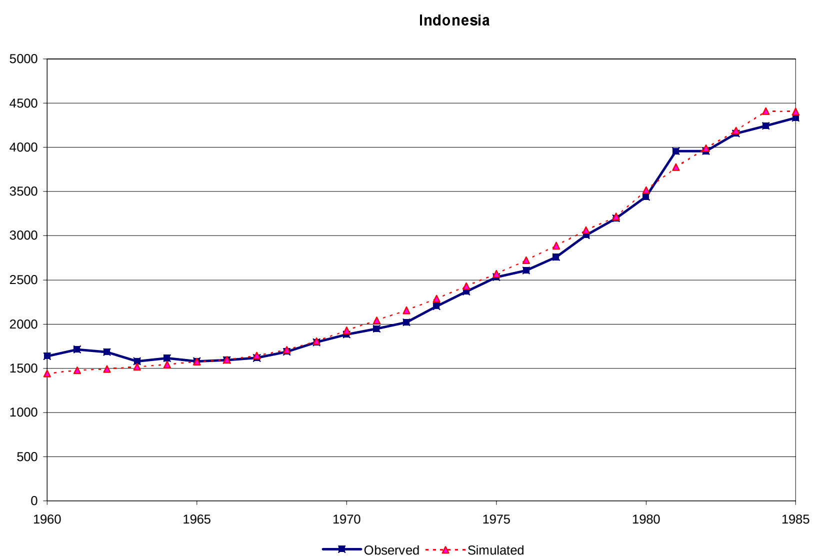

Figure 4: Actual and simulated output per worker (Indonesia)

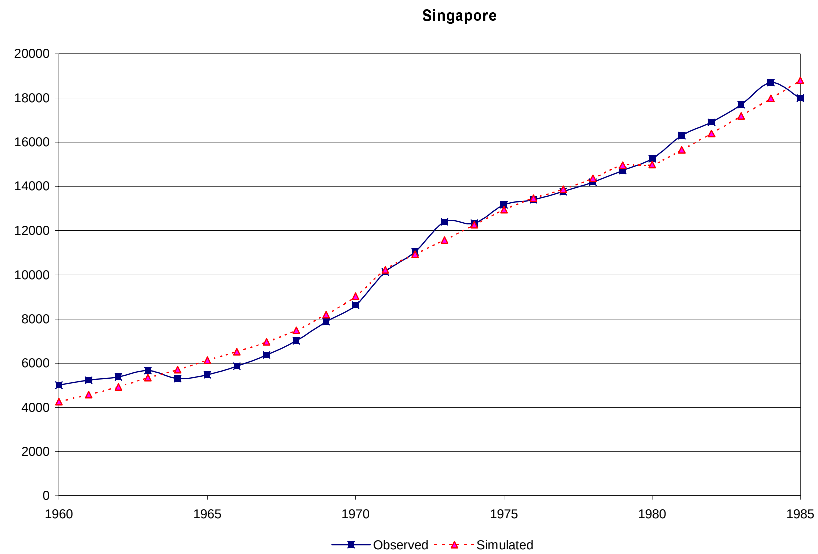

Figure 5: Actual and simulated output per worker (Singapore)

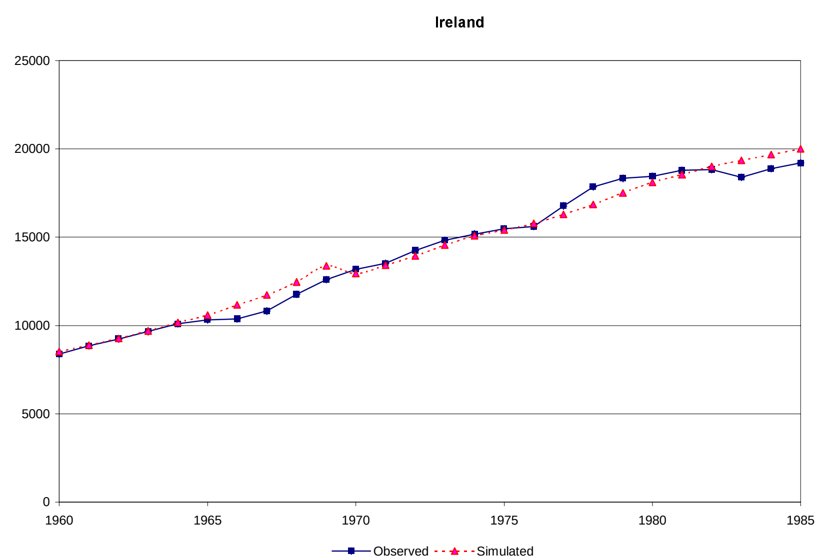

Figure 6: Actual and simulated output per worker (Ireland)

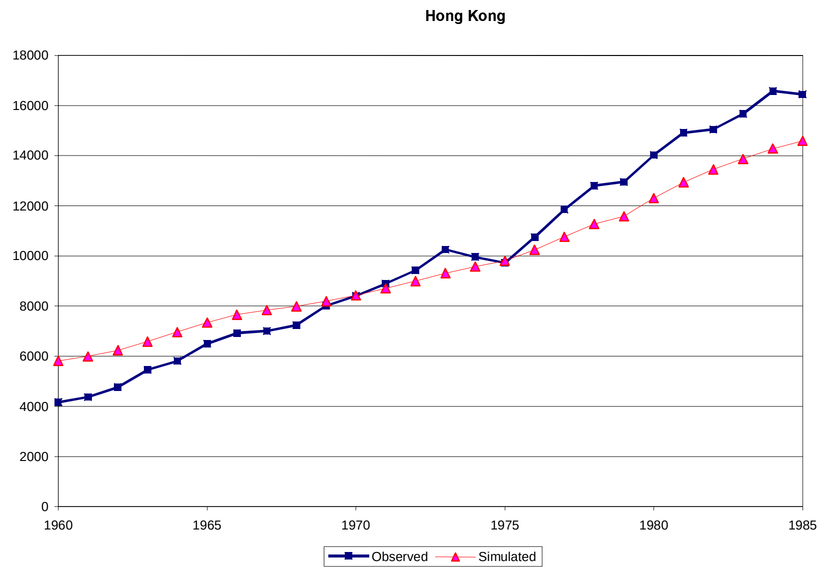

Figure 7: Actual and simulated output per worker (Hong Kong)

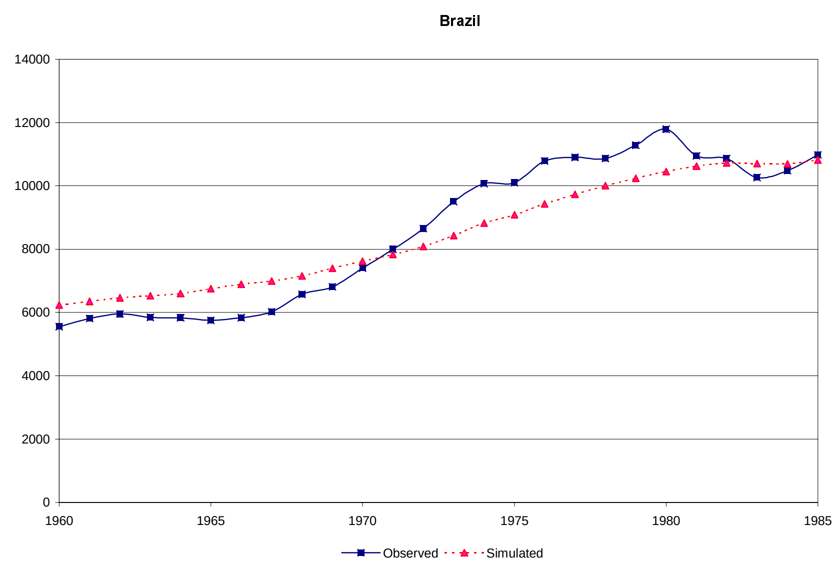

Figure 8: Actual and simulated output per worker (Brazil)

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

Parameters/Statistics	Depreciation Rates (δ)				
	3%	6%	9%	12%	15%
α	0.4038	0.4124	0.4195	0.4183	0.4176
(t-ratio)	(66.58)	(70.62)	(71.92)	(73.80)	(75.00)
ϕ	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 $\theta = 1$ (p-value)	0.7520	0.7153	0.7517	0.9112	0.7743
Box-Cox $\theta = 0$ (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 2: Estimates of the Extended Neoclassical Growth Model - Double-Log Model

Parameters/Statistics	Depreciation Rates (δ)				
	3%	6%	9%	12%	15%
α	0.4097	0.4217	0.4325	0.4287	0.4273
(t-ratio)	(68.77)	(72.95)	(74.60)	(75.59)	(76.09)
β	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 $\theta = 1$ (p-value)	0.7520	0.7153	0.7517	0.9112	0.7743
Box-Cox $\theta = 0$ (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 3: Estimates of the Extended Neoclassical Growth Model with no Fixed Effects

Parameters/Statistics	Depreciation Rates (δ)				
	3%	6%	9%	12%	15%
α	0.5143	0.5706	0.6023	0.6043	0.5982
(t-ratio)	(187.52)	(174.29)	(171.73)	(171.71)	(166.51)
β	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 Mincerian Growth Model with no Fixed Effects

Parameters/Statistics	Depreciation Rates (δ)				
	3%	6%	9%	12%	15%
α	0.5154	0.5665	0.5931	0.5967	0.5979
(t-ratio)	(193.32)	(181.32)	(194.15)	(192.25)	(189.65)
ϕ	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 5: Variance Decomposition of Output per Worker in Terms of Different Factors

Variance Decomp. of $\ln y_i$	% of variance due to factor related to					
	A_i	$\left(\frac{K_i}{Y_i}\right)$	τ_i	k_i	h_i	$\sum Cov.$
"Naive"	21%			49%	2%	28%
Equation (15)	54%		21%		5%	20%
Equation (17)	45%	45%			1%	9%
5 richest and poorest (Eq. (15))	43%		21%		5%	31%

Table 6: Relative Productivity Estimate for Selected Countries (U.S.=1.00)

Country	RelativeProductivity
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 7: Country Classification According to Different Factors

Group	Features	Number of 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 Underducated	4	1	3849
5	Productive, Distorcive and Underducated	16	2	2793
6	Unproductive, Distorcive and Educated	3	2	2289
7	Unproductive, Non-distorcive and Underducated	5	2	1934
8	Unproductive, Distorcive and Underducated	25	3	1130

Table 8: Groups of countries according to relative position with respect to average productivity, distortion and education

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, N. Zealand
Group 2: Unproductive, Non-distorcive and Educated: Japan, Korea Rep., Malaysia, Taiwan, Cyprus, Finland, Yugoslavia, Czechoslovakia, Romania, U.S.S.R., Panama, Ecuador, Guyana
Group 3: Productive, Distorcive and Educated: Barbados, Trinidad&Tobago, Chile, Peru, Uruguay, Venezuela
Group 4: Productive, Non-distorcive and Underducated: Algeria, South Africa, Brazil, Portugal
Group 5: Productive, Distorcive and Underducated: 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 Underducated: Botswana, Zambia, Zimbabwe, Jamaica, Reunion
Group 8: Unproductive, Distorcive and Underducated: 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

Table 9: Relative Output of Selected Countries in Counter-Factual Analysis

Country	Y_i/Y_{US} (Uncorrected)	Y_i/Y_{US} $(\tau_i = \tau_{US})$	Y_i/Y_{US} $(h_i = h_{US}, \text{and } \tau_i = \tau_{US})$
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