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Working Paper

Second thoughts on development accounting

Kieler Arbeitspapiere, No. 895

Provided in cooperation with:
Institut für Weltwirtschaft (IfW)

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Kiel Working Paper No. 895

Second Thoughts on Development Accounting

by

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December 1998

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ABSTRACT

We estimate the relative roles of factor inputs and productivity in explaining the level of economic development, which is measured as output per worker. For a large sample of countries, we show that alternative identifying productivity assumptions and alternative measures of human capital have a large impact on the relative weights of factor inputs and productivity in a decomposition of output per worker. For a sample of OECD countries, we find that productivity has almost no role in explaining cross-country differences in output per worker. This result supports the reasoning of a traditional neoclassical growth model.

JEL: O4

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1. Introduction and Summary

International differences in output per worker are difficult to explain by differences in factor endowments, at least according to recent studies of development accounting by Hall and Jones (1998), Klenow and Rodríguez-Clare (1997), and Prescott (1998). These studies find large cross-country productivity residuals after controlling for physical and human capital. This finding questions the usefulness of the traditional neoclassical model of growth and development, which does not provide an explanation for residual productivity differences.

We argue that claims of the demise of the traditional neoclassical model of growth and development are premature. We show that the size of the productivity residual crucially depends on an identifying assumption about the specific factor-augmenting properties of productivity. The difficulty is that it is impossible to discriminate between the alternative assumptions of Hicks-neutral and Harrod-neutral productivity under the standard restrictions imposed on the production function in virtually all applied analyses. Hence, residual productivity differences estimated by standard development-accounting methods always reflect an untestable a priori assumption, which necessarily influences the relative weight of factor inputs and productivity in a decomposition of output per worker (Section 2).

In addition, large international productivity residuals may reflect measurement errors or omitted variables. The leading candidate for mismeasurement is the stock of human capital. We improve the measurement of human capital by taking account of cross-country differences in schooling systems, in rates of return to education, and in quality of education. If improved measures of human capital can explain a larger fraction of international income differences, this will necessarily reduce the residual productivity measure, independent of the chosen productivity assumption (Section 3).

In our decomposition of output per worker, we show the quantitative impact of alternative identifying assumptions and of alternative measures of the stock of human capital on residual productivity measures. We find that alternative identifying assumptions matter for the relative weight of residual productivity in explaining international differences of output per worker. We also find that an alternative measure of human capital substantially reduces the weight of residual productivity (Section 4).

Notwithstanding these revisions, we find that, for a large sample of countries, residual productivity differences remain an important determinant of international differences in output per worker. But looking only at the OECD countries, which share a set of rather similar economic policies and appear to provide the most reliable data, almost all income differences can be explained by differences in factor inputs rather than by residual productivity differences. Thus, for the OECD countries, the traditional neoclassical growth model seems to fit the facts quite well.

2. Identifying the Productivity Assumption

Decomposing output per worker into the relative contributions of different inputs requires the specification of a production function. On the input side, the standard practice is to differentiate measurable factor inputs, such as capital and labor, from a residual term, which is not directly observable. In the following, we call this residual term productivity; in other applications, the residual is sometimes referred to as total factor productivity or technology.

The inherent problem of a decomposition of output into factor inputs and productivity is that it is impossible to discriminate empirically between changes in factor inputs that reflect a movement along a given production function and changes in productivity that reflect a shift of the production function. Because productivity is not observed directly, one cannot conclude from observations of output per worker and factor inputs what the shape of the production function is, and therefore, *how* productivity might have shifted the production function (Nelson 1973).

This problem is also present in development accounting studies, where output and factor inputs are measured at a given point in time. The reason is that any difference between output and the sum of weighted factor inputs, which equals residual productivity, obviously depends on the weighting scheme employed. But the weighting scheme itself depends on an assumption about the specific neutrality properties of productivity (the residual). Within the model, it is a question of theory, not empirics, which weighting scheme has to be preferred to possible alternatives. We call this weighting scheme the identifying productivity assumption.

In the older literature on growth accounting,[1] the standard practice was to assume Hicks-neutral productivity, while more recent papers on development accounting claim that it is more appropriate to assume Harrod-neutral productivity. To compare these identifying assumptions, consider a most simple Cobb-Douglas production function

$$(1) \qquad Y = K^{\alpha} L^{(1-\alpha)} e^{\lambda} \quad ,$$

where Y is the level of output, K is the stock of physical capital, L is labor used in production, and e^{λ} denotes productivity. It remains to interpret λ in terms of alternative neutrality concepts of productivity.[2]

Hicks-neutral productivity would leave unchanged the relation between the marginal product of labor and the marginal product of capital (the wage-rental ratio) for any given capital-labor ratio. This amounts to a proportionate increase in K and L at a common rate, m:

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1 For a recent review, see Barro (1998).

2 On the following, see, e.g., Allen (1967).

(2) $$Y = \left(e^{m}K\right)^{\alpha}\left(e^{m}L\right)^{(1-\alpha)} \quad ,$$

which is equal to equation (1) with $\lambda = m$.

Harrod-neutral productivity would leave unchanged the marginal product of capital (the rental rate of capital) for any given capital-output ratio. This amounts to a purely labor-augmenting effect of productivity, n:

(3) $$Y = K^{\alpha}\left(e^{n}L\right)^{(1-\alpha)} \quad ,$$

which is equal to equation (1) with $\lambda = n\,(1 - \alpha)$.

It follows that Hicks-neutral productivity is equal to Harrod-neutral productivity raised to the power of $(1 - \alpha)$ for $m = n$. That is, assuming Harrod-neutral productivity implicitly gives a larger weight to productivity in a decomposition of output per worker than assuming Hicks-neutral productivity. For instance, if log output equals 1 and Harrod-neutral productivity is found to explain 90 percent of log output, then, all other things equal, Hicks-neutral productivity only explains 60 percent of log output if $\alpha = 1/3$. This example shows that the identifying productivity assumption matters for the results of a decomposition of output per worker, and suggests that the assumption of Harrod-neutrality is one of the reasons why recent studies (Hall and Jones 1998, Klenow and Rodríguez-Clare 1997) find a relatively large contribution of productivity.

The motivation for using Harrod-neutrality instead of Hicks-neutrality is based on growth theory. The appropriate identifying productivity assumption must be consistent with two steady-state requirements of the neoclassical growth model. First, since all the variables in the model have to grow at the same rate in the steady state, the capital-output ratio must remain constant along a balanced steady-state growth path. Second, based on empirical evidence, the factor shares of capital and labor must also remain constant in the steady state. Barro and Sala-i-Martin (1995) point out that Harrod-neutral productivity change turns out to be the only identifying productivity assumption that is consistent with these conditions of a steady state.

While this assertion is true for a general growth model with no specific restrictions imposed on the production function, it is a well-known fact that it does not hold for a Cobb-Douglas production function. Since the Cobb-Douglas production function implies a unit elasticity of substitution, factor shares remain constant for any capital-labor ratio and for any capital-output ratio. This is why the Cobb-Douglas production function has unequivocal neutrality properties (Hahn and Matthews 1964) with regard to productivity shifts.[3]

3 Barro and Sala-i-Martin (1995) claim to prove that productivity shifts must be Harrod-neutral in order for the neoclassical model to have a steady state, but their formal proof is in fact a demonstration of the steady-state compatibility of both Harrod- and Hicks-neutral productivity shifts for the Cobb-Douglas case.

When the production function used in a development or growth accounting exercise is Cobb-Douglas, as happens to be the case in most applied work, neoclassical growth theory does not help to decide whether Hicks- or Harrod-neutrality should be used as the identifying productivity assumption. This insight has long been known, but it seems to have been overlooked in recent contributions on development accounting. In our decomposition of output per worker in Section 4, we always present the relative contribution of both Harrod- and Hicks-neutral productivity to illustrate the significance of the choice of the identifying productivity assumption in empirical work.

3. Measuring Human Capital

Human capital is obviously linked to the factor input of labor, and is therefore best modeled as a factor that directly improves the quality of the workforce rather than as an independent factor of production. In empirical work, human capital is usually proxied by schooling. Average years of schooling (*S*) can be used to construct a human-capital augmented measure of labor given by

(4) $$H = e^{\phi(S)}L \quad ,$$

where *H* is the stock of human capital and the function $\phi(S)$ reflects the efficiency of a unit of labor with *S* years of schooling relative to one with no schooling.

As suggested by Bils and Klenow (1996), this functional form is the appropriate way to incorporate years of schooling into an aggregate production function because it has a straightforward interpretation. First, if $\phi(S) = 0$, a standard production function with undifferentiated labor such as equation (1) would apply. Second, the efficiency of S years of schooling depends on the rate of return to education, as suggested by microeconometric evidence based on the Mincerian wage equation. In this equation, the rate of return turns out to be the derivative $\phi'(S)$, which can be estimated empirically as the regression coefficient on S. Thus, average years of education can be combined with empirical rates of return to education to derive country-specific estimates of the stock of human capital.

For our estimates of the stock of human capital, we use average years of education in the population aged 25 and over as calculated by Barro and Lee (1996). By contrast to Hall and Jones (1998), we use *social* rates of return to education rather than private rates of return because we want to assess the economy-wide contribution of human capital in our decomposition of output per worker. Social rates of return are more appropriate for this purpose since they take all expenditures on education into account. As our measure of social rates, we employ estimates of returns to education based on the so-called “full” or “elaborate” method of calculation, as reported by Psacharopoulos (1994).

This method is considered to be the most appropriate because it takes into account the most important part of the early earning history of individuals.

Our measure of human capital differs from Hall and Jones (1998) in two other ways. First, we use *country-specific* rates of return to schooling at each level of schooling rather than uniform rates for all countries. Second, instead of assuming the same duration for primary and secondary education across all countries, we use country-specific data on the duration of each level of education as reported in UNESCO's Statistical Yearbook.[4] We combine this information with country-specific rates of return to schooling at the primary, secondary, and higher level reported by Psacharopoulos (1994) to calculate $\phi(S)$ in equation (4) according to

(5)

$$\phi(S_i) = \begin{cases} r_i^{Pri} * S_i & \text{if } S_i \le Pri_i \\ r_i^{Pri} * Pri_i + r_i^{Sec} * (S_i - Pri_i) & \text{if } Pri_i < S_i \le Pri_i + Sec_i \\ r_i^{Pri} * Pri_i + r_i^{Sec} * Sec_i + r_i^{High} * (S_i - Pri_i - Sec_i) & \text{if } S_i > Pri_i + Sec_i \end{cases}$$

where r_i^{Pri}, r_i^{Sec} and r_i^{High} are the social rates of return to primary, secondary, and higher schooling in country i; Pri_i is the duration of the primary level of

4 We take the first level of secondary schooling as reported in the UNESCO yearbook as our measure of secondary level of schooling. For countries that do not distinguish between the first and second stage of secondary schooling, we allocate half the years reported for total secondary education to the first stage.

schooling; Sec_i is the duration of the first stage of secondary level schooling; and S_i is average years of educational attainment.

The specification of equation (4) can be further improved by including a measure of the quality of education. As is almost self-evident, a year of education in, say, Tanzania should be valued differently than a year of education in, say, Japan. Such a difference would only be appropriately captured by the respective rates of return if labor were internationally mobile. Since labor is largely immobile internationally, we consider international differences in the quality of education as a separate determinant of the stock of human capital along with international differences in rates of return. If the efficiency of the workforce is measured more accurately, the contribution of human-capital augmented labor can be isolated more precisely. An improved measure of human capital in turn will improve the residual productivity measure in a decomposition of output per worker.

We employ a measure of the quality of education suggested by Hanushek and Kim (1995). They construct their quality measure for each country by using a weighted average of various test scores, mainly in mathematics and natural sciences, reported by standardized international student-achievement tests. Such tests have been conducted by the International Association for the Evaluation of Educational Achievement (IEA) and other international organizations for many countries and various years.

To use this measure in our human-capital calculation, we normalize the quality measure for each country relative to the measure for the United States. This variable can be incorporated into our human-capital estimate as

$$(6) \qquad H_Q = e^{\phi(S \cdot Q)} L \quad ,$$

where Q is the quality index of education reported by Hanushek and Kim (1995)[5] relative to the US level.

Our modification of equation (4) is based on the assumption that human-capital formation is given by multiplying quantity of schooling by quality of schooling. This method of incorporating the quality measure into equation (6) can be justified if estimated regression coefficients on quantity and quality do not differ in a regression where the log values of these variables enter separately on the right-hand side of a conventional production function. This is confirmed by the results of Hanushek and Kim (1995).

4. Empirical Results

4.1 Decomposing Output per Worker

Our empirical interest is in a decomposition of output per worker into contributions of factor inputs and productivity, controlling for the impact of alternative productivity assumptions and alternative measurements of the stock

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5 For our calculation, we use their variable $QL2*$.

of human capital. With Harrod-neutral productivity, equation (3) can be rewritten in terms of output per worker $y \equiv Y / L$ in country i as

$$(7) \qquad y_i = \left(\frac{k_i}{y_i}\right)^{\alpha/(1-\alpha)} h_i A_i^{Harrod} \ ,$$

with $k \equiv K / L$ as the capital-labor ratio, $h \equiv H / L$ as human capital-labor ratio, and $A_i^{Harrod} = e^n$. With Hicks-neutral productivity, equation (2) can be rewritten as

$$(8) \qquad y_i = k_i^{\alpha} h_i^{(1-\alpha)} A_i^{Hicks} \ ,$$

with $A_i^{Hicks} = e^m$.

We assume a production elasticity of physical capital of $\alpha = 1/3$, which is the standard figure used for parameterization in the literature. This production elasticity broadly resembles the share of capital in factor income as reported in national income accounts of developed countries (Maddison 1987). The same capital share seems to apply for developing countries as well if the labor income of the self-employed and other proprietors is properly accounted for (Gollin 1998).

We use two methods to summarize the relative contributions of factor inputs and productivity in our decomposition of output per worker across countries. The first method, which we call the "covariance measure", was proposed by Klenow and Rodríguez-Clare (1997). The variance of *ln(y)* is decomposed into one covariance term with *ln(X)*, where *X* is a composite measure of physical- and human-capital inputs, and another covariance term with *ln(A)* according to

(9) $$\mathrm{var}(\ln(y)) = \mathrm{cov}(\ln(y), \ln(y)) = \mathrm{cov}(\ln(y), \ln(X)) + \mathrm{cov}(\ln(y), \ln(A)) \quad ,$$

so that

(10) $$\frac{\mathrm{cov}(\ln(y), \ln(X))}{\mathrm{var}(\ln(y))} + \frac{\mathrm{cov}(\ln(y), \ln(A))}{\mathrm{var}(\ln(y))} = 1 \cdot$$

This method allows us to present results as a percentage distribution. That is, applying this method gives the respective average fraction of output per worker across countries that can be explained by factor inputs, leaving the rest to be explained by residual productivity.

The second method, which we call the "five-country measure", is adapted from Hall and Jones (1998). This measure shows how much of the difference in output per worker between the five countries with the highest output per worker and the five countries with the lowest output per worker (based on a geometric average) is due to differences in factor inputs and how much is due to differences in productivity. As before, by taking log values, we can break up the variation in output per worker into a fraction that can be explained by factor inputs and a residual fraction that represents productivity:

(11) $$\frac{\ln\left[\left(\prod_{i=1}^{5} X_i \Big/ \prod_{j=n-4}^{n} X_j\right)^{1/5}\right]}{\ln\left[\left(\prod_{i=1}^{5} y_i \Big/ \prod_{j=n-4}^{n} y_j\right)^{1/5}\right]} + \frac{\ln\left[\left(\prod_{i=1}^{5} A_i \Big/ \prod_{j=n-4}^{n} A_j\right)^{1/5}\right]}{\ln\left[\left(\prod_{i=1}^{5} y_i \Big/ \prod_{j=n-4}^{n} y_j\right)^{1/5}\right]} = 1 \quad ,$$

where n is the sample size and countries i, ..., j, ..., n are ranked according to output per worker. By focusing on the highest and the lowest part of the sample distribution, we use this measure to control for the robustness of the results derived with equation (10).

Both measures reflect the different impact of Harrod- and Hicks-neutral productivity in a decomposition of output per worker (Section 2). As is shown in the appendix, the share of Hicks-neutral productivity in explaining output differences is equal to $(1-\alpha)$ times the share of Harrod-neutral productivity. Because of the adding-up restriction imposed in equations (10) and (11), estimating the contribution of factor inputs under Harrod-neutrality also identifies the contribution of productivity under Harrod-neutrality and of factor inputs and productivity under Hicks-neutrality.

4.2 Data

The data on y, K , and L are derived from PWT (1994). Output per worker y is measured in 1990 or the next available year. The 1990 value of physical capital K is constructed by the perpetual inventory method based on annual investment rates and an assumed depreciation rate of 6 percent. The initial value for K is estimated by $I_t / (g_{t+10} + \delta)$, where I_t is the first year for which investment data are available, g_{t+10} is the average growth rate of investment in the subsequent decade, and δ is the depreciation rate (see Hall and Jones 1998). The figures for labor L in 1990 are derived by multiplying per capita output with population and dividing by output per worker.

Our sample is determined by the availability of data on investment rates and on output per worker. For this sample of countries, we construct our two measures of human capital using average years of schooling, rates of return to education, and the quality index of schooling as described in Section 3.

In the calculation of the stock of human capital, we impute data for a number of countries. This is done by taking the mean of the respective regional average and the respective income-group average to replace any missing value for an individual country, using the World Bank’s classification of countries by income and region (World Bank 1992). The regions used are Asia, Latin America, Sub-Saharan Africa, North Africa, Middle East, Eastern Europe, and OECD, and the income groups are low, lower-middle, upper-middle, and high income.

We present our basic data in Table A1 in the appendix. The data are presented in per-worker terms and relative to the US level to allow for an easy comparison across countries. Countries are ranked according to output per worker. Various dummy variables indicate which data are imputed. All in all, our results tend to confirm that rich countries have a higher stock of physical capital per worker and a higher stock of human capital per worker than poor countries.

For a limited number of countries, we find surprising results. For example, Oman and Puerto Rico are ranked rather high with respect to output per worker. For Oman, this reflects its huge endowment of oil and other natural resources. The same applies to other resource-rich countries.

Since our results are not sensitive to excluding resource-rich countries from the sample, the relatively high ranking of these countries does not influence our aggregate findings. Puerto Rico is a different case, but can also be deleted from the aggregate sample without changing the results. Its output per worker is likely to be overstated due to internal pricing of US firms located in Puerto Rico to take advantage of lower taxes, as suggested by Hall and Jones (1998).

The large figures on quality-adjusted human capital per worker for countries such as New Zealand, Hong Kong, and Poland are mainly due to their superior performance in student-achievement tests relative to the United States. The relatively high measures of human capital of Eastern European countries are due to their high reported average years of schooling and student-achievement test scores. In some centrally-planned economies such as the former Soviet Union and China, non-representative sample selection may bias our results upwards.

Another source of surprising results is the country-specific data on rates of return to primary education reported by Psacharopoulos (1994). This measure ranges from 2 percent for Yemen to 66 percent for Uganda. Yemen's low figure makes it the country with the lowest human-capital measure in the sample, while Morocco's rate of return on primary investment of 50.5 percent (as compared to its regional average of 15.5 percent and its income-group average of 18.2 percent) explains its high measure of human capital. The surprisingly large difference in the value of human capital between Singapore and Hong Kong is mainly explained by the large difference in their rates of return to primary education (6.6 percent for Singapore and an imputed 19.9 percent for Hong Kong), and only to a lesser extent by differences in average years of schooling (5.47 years for Singapore and 8.37 years for Hong Kong). Nevertheless, all our aggregate results are insensitive to substituting outlier values of rates of return to education by average regional and income-group values.

4.3 Full-Sample Results

In order to provide a point of reference, we begin our decomposition of output per worker with a replication of the results of Hall and Jones (1998) with updated 1990 data and a slightly different sample of countries.[6] With their dataset, Hall and Jones (1998) find that 60 percent of the international variation

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6 Hall and Jones (1998) use 1988 data except for average years of education, where they use 1985 data, and their sample consists of 127 coutries, while our sample consists of 131 countries. We do not subtract value added in the mining sector, which includes oil and gas. Their subtraction of the value added of mining from output was intended as a measure to control for large differences in natural resources across countries, which could bias the residual productivity results. However, correcting output but not inputs may prove to be a source of additional bias since mining is a physical- and human-capital intensive sector.

in output per worker is due to international differences in productivity, given that Harrod-neutral productivity prevails.[7] The first row in Table 1, denoted HJ, replicates this finding almost perfectly. According to these figures, when there is 1 percent higher output per worker in one country relative to the mean of the whole sample with Harrod-neutral productivity, then the conditional expectation of X_{Harrod} is 0.41 percent higher and the conditional expectation of A_{Harrod} is 0.59 percent higher. With Hicks-neutral productivity, the conditional expectation of X_{Hicks} is 0.61 percent higher and the conditional expectation of A_{Hicks} is 0.39 percent higher.

This result of the covariance measure indicates that the small modifications we have made with respect to the measurement of output, sample size, and updating the dataset to 1990 values do not have an impact on the results. What matters for the results at this stage is the identifying technology assumption. Assuming Harrod-neutrality, the impact of physical capital and human capital is relatively small in explaining international differences in output per worker. But

7 This result is due to an application of the covariance measure to the data reported by Hall and Jones (1998). Detailed results are available on request.

Table 1 — Factor Inputs versus Productivity: Covariance Measure

$$\frac{\operatorname{cov}(\ln(y),\ln(Z))}{\operatorname{var}(\ln(y))} \text{ with } Z \text{ given in each column}$$

Identifying Productivity Assumption	Harrod-Neutrality		Hicks-Neutrality	
	Factor Inputs X	Productivity A	Factor Inputs X	Productivity A
HJ	0.41	0.59	0.61	0.39
GRW1	0.40	0.60	0.60	0.40
GRW2	0.49	0.51	0.66	0.34

Notes: HJ = Based on *Hall/Jones* methodology to calculate H, with updated data but without mining adjustment. — GRW1 = Based on our measure of H. — GRW2 = Based on our measure of H_Q.

assuming Hicks-neutrality reverses this result to some extent, giving a larger weight to factor inputs.

The second row in Table 1, denoted GRW1, shows that our first measure of the stock of human capital does not change this result. However, the sample mean of human capital per worker rises substantially from 1.91 (0.57) in HJ to 2.44 (1.03) in GRW1 (standard deviations in parentheses). The correlation coefficient of h_{HJ} and h_{GRW1} is 0.70, so that the apparent constancy of the results for the full sample may mask differences across subsamples.

The third row of Table 1, denoted GRW2, reports the results for our second human-capital measure, which accounts for international differences in the quality of schooling. This augmented measure of the stock of human capital substantially reduces the explanatory power of residual productivity. Assuming

Harrod-neutral productivity, the covariance measure suggests that about 50 percent of the international variation of output per worker can be explained by international differences in factor inputs, compared to 40 percent as before. Assuming Hicks-neutral productivity, as much as two thirds of the international differences in output per worker can be attributed to differences in factor inputs.

These results are largely confirmed by the five-country measure (Table 2). If human capital is measured without an adjustment for differences in the quality of schooling, factor inputs explain 43-62 percent of the international variation in output per worker, depending on the identifying productivity assumption. Once our measure of human capital includes international differences in the quality of schooling, factor inputs explain about 50-67 percent of the international variation in output per worker.

Another way to check the robustness of our results[8] is to exclude countries in which value added in the mining sector accounts for more than 20 or even 10 percent of total value added. In such a revised sample, the estimated relative contributions of factor inputs and productivity do not change by more than 2 percentage points compared to the previous estimates. Therefore, international differences in natural-resource endowments do not influence our findings significantly.

8 Detailed results of the following tests of robustness are available on request.

Table 2 — Factor Inputs versus Productivity: Five-Country Measure

$$\ln\left(\left(\prod_{i=1}^{5} Z_i \Big/ \prod_{j=n-4}^{n} Z_j\right)^{1/5}\right) \Big/ \ln\left(\left(\prod_{i=1}^{5} y_i \Big/ \prod_{j=n-4}^{n} y_j\right)^{1/5}\right)$$

with *n* = sample size, countries *i*, ..., *j*, ..., *n* ranked according to *y*, and *Z* given in each column

Identifying Productivity Assumption	Harrod-Neutrality		Hicks-Neutrality	
	Factor Inputs *X*	Productivity *A*	Factor Inputs *X*	Productivity *A*
HJ	0.42	0.58	0.61	0.39
GRW1	0.43	0.57	0.62	0.38
GRW2	0.50	0.50	0.67	0.33

Notes: HJ = Based on *Hall/Jones* methodology to calculate *H*, with updated data but without mining adjustment. — GRW1 = Based on our measure of *H*. — GRW2 = Based on our measure of H_Q.

In addition, the explanatory power of factor inputs is not reduced if we exclude countries with imputed data on the human-capital measure. The results are also robust to reducing the sample to only those countries which have participated at least once in the benchmark studies underlying PWT (1994), for which the data is more reliable. The same holds if we delete countries with imputed data on the human-capital measure from this subsample of countries.

Our results also reveal that the main objection which both Hall and Jones (1998) and Klenow and Rodríguez-Clare (1997) raise against the methodology used by Mankiw et al. (1992) has to be qualified. Assuming Harrod-neutral productivity, Mankiw et al. (1992) estimate a regression equation which requires the identifying assumption that *ln (X)* be orthogonal to *ln (A)*. But if factor inputs and productivity are positively correlated, this assumption is not justified. As shown in Table 3, we find that, with our quality-adjusted human-capital measure, Harrod-neutral productivity is only weakly correlated with the capital-output ratio and uncorrelated with human capital per worker, which supports the identifying assumption made by Mankiw et al. (1992). However, in our data, productivity still remains correlated with output per worker, so that the residual in a regression analysis will not be white noise.

Table 3 — Correlation between Output, Inputs, and Productivity

	y	$(K/Y)^{\alpha/(1-\alpha)}$	h	A_{Harrod}
Correlation with output per worker				
HJ	1	0.654	0.824	0.884
GRW1	1	0.654	0.584	0.841
GRW2	1	0.654	0.625	0.739
Correlation with productivity				
HJ	0.884	0.262	0.529	1
GRW1	0.841	0.265	0.128	1
GRW2	0.739	0.162	-0.004	1

Notes: Numbers reported are correlation coefficients; all variables measured in logs. — HJ = Based on *Hall/Jones* methodology to calculate H, with updated data but without mining adjustment. — GRW1 = Based on our measure of H. — GRW2 = Based on our measure of H_Q.

Klenow and Rodríguez-Clare (1997) claim in their study of development accounting that the so-called "Neoclassical Revival" originated by Mankiw et al. (1992) and others has gone too far. They report a relatively strong role for international productivity differences and attribute about one half to two thirds of the international variation in output per worker to productivity differences.

They comment that they are unable to distinguish between these two estimates. This is because they do not take into account *observed* differences in the quality of schooling. Another problem is that they ignore the high sensitivity of their results to the identifying productivity assumption, despite using a Cobb-Douglas production function.

By contrast, our results do take account of a direct measure of quality of schooling and recognize the arbitrariness of the identifying productivity assumption. We find a relatively strong role for international differences in factor inputs and attribute about one half to two thirds of the international variation in output per worker to differences in factor inputs. Therefore, the conclusion of Klenow and Rodríguez-Clare (1997) that "productivity differences are the dominant source of the large international dispersion in levels […] of output per worker" may have gone too far. But the same may be said for the "Neoclassical Revival" in growth economics: If international differences in residual productivity explain up to 50 percent of the international variation in output per worker, the traditional neoclassical growth model does not help much in understanding the data.

4.4 OECD-Sample Results

The second sample we consider is that of OECD countries.[9] The advantage of this sample is that the data is of a relatively high quality and that omitted country-specific factors should not vary substantially between these countries. OECD countries are similar to one another in that they all exhibit a relatively high degree of openness, have market-friendly policies, and are able to access technology levels near the world technology frontier.

As our results based on the covariance measure show (Table 4), factor inputs apparently explain a larger fraction of output per worker than in our full sample. Using our first measure of human capital, GRW1, already increases the explanatory power of factor inputs as compared to the measure used by Hall and Jones (1998), HJ. Using our quality-adjusted human capital measure, GRW2, we find that about 90 percent of the differences in output per worker across OECD countries can be explained by differences in factor inputs. Differences in productivity contribute only about 10 percent to differences in output per worker. Since the fraction of output per worker explained by factor inputs is so large, this result is not very sensitive to the identifying productivity assumption.[10]

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9 This sample consists of 23 countries: all OECD countries in 1990 excluding Luxembourg, for which no schooling attainment data was available.

10 Both the results of the five-country measure (Table A2) and the low correlation coefficient between output per worker and productivity (both in logs) of 0.10 confirm the results of the covariance measure.

Table 4 — Factor Inputs versus Productivity in the OECD: Covariance Measure

$\frac{\text{cov}(\ln(y),\ln(Z))}{\text{var}(\ln(y))}$ with Z given in each column

Identifying Productivity Assumption	Harrod-Neutrality		Hicks-Neutrality	
	Factor Inputs X	Productivity A	Factor Inputs X	Productivity A
HJ	0.59	0.41	0.72	0.28
GRW1	0.66	0.34	0.78	0.22
GRW2	0.87	0.13	0.91	0.09

Notes: HJ = Based on *Hall/Jones* methodology to calculate H, with updated data but without mining adjustment. — GRW1 = Based on our measure of H. — GRW2 = Based on our measure of H_Q.

A comparison of the results using the full sample vs. the OECD sample suggests the following interpretation. For the countries for which data is most reliable, differences in physical- and human-capital inputs suffice to explain differences in output per worker. The higher explanatory power of productivity differences in the full sample may thus, to some degree, reflect poorer quality of data for many non-OECD countries.

Furthermore, OECD countries should be expected to produce near the world technology frontier. In many of the countries with low output per worker, entrepreneurs and workers might be hindered to use the best available technology by bad economic policies or rigid institutional frameworks. This might be another reason why we find that residual productivity does explain a fair amount of the difference in output per worker in our full sample.

5. Conclusion

Recent contributions to development accounting have gone one step too far by overstating the importance of productivity differences in explaining differences in output per worker. International productivity differences, which are estimated as residuals, always reflect a mixture of untestable theoretical identifying assumptions, errors due to using imperfect measures of the true variables, and data recording errors, the relative contributions of which are difficult to delineate. We show that the impact of alternative identifying productivity assumptions and alternative methods of measuring human capital is potentially large. Hence, recent calls for a new theory of total factor productivity should at least be accompanied by calls for improved measurement of factor inputs. In the meantime, the traditional neoclassical growth model still appears to be a valid workhorse for empirical development accounting.

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Appendix

A. Decomposing Output per Worker with Hicks- and Harrod-neutrality

1. Let *C (A)* denote the covariance measure of *A*:

$$C(A) \equiv \frac{\operatorname{cov}(\ln(y), \ln(A))}{\operatorname{var}(\ln(y))} \quad .$$

The numerator of *C* (A^{Hicks}) can be transformed as follows:

$$\begin{aligned}
\operatorname{cov}\left(\ln(y), \ln\left(A^{Hicks}\right)\right) &= \frac{1}{n}\sum_{i=1}^{n}\left\{\left[\ln(y_i) - \frac{1}{n}\sum_{j=1}^{n}\ln(y_j)\right] * \left[\ln\left(A_i^{Hicks}\right) - \frac{1}{n}\sum_{j=1}^{n}\ln\left(A_j^{Hicks}\right)\right]\right\} \\
&= \frac{1}{n}\sum_{i=1}^{n}\left\{\left[\ln(y_i) - \frac{1}{n}\sum_{j=1}^{n}\ln(y_j)\right] * \left[\ln\left(\left(A_i^{Harrod}\right)^{(1-\alpha)}\right) - \frac{1}{n}\sum_{j=1}^{n}\ln\left(\left(A_j^{Harrod}\right)^{(1-\alpha)}\right)\right]\right\} \\
&= (1-\alpha)\frac{1}{n}\sum_{i=1}^{n}\left\{\left[\ln(y_i) - \frac{1}{n}\sum_{j=1}^{n}\ln(y_j)\right] * \left[\ln\left(A_i^{Harrod}\right) - \frac{1}{n}\sum_{j=1}^{n}\ln\left(A_j^{Harrod}\right)\right]\right\} \\
&= (1-\alpha) * \operatorname{cov}\left(\ln(y), \ln\left(A^{Harrod}\right)\right)
\end{aligned}$$

so that

$$C\left(A^{Hicks}\right) \equiv \frac{\operatorname{cov}\left(\ln(y), \ln\left(A^{Hicks}\right)\right)}{\operatorname{var}(\ln(y))} = \frac{(1-\alpha) * \operatorname{cov}\left(\ln(y), \ln\left(A^{Harrod}\right)\right)}{\operatorname{var}(\ln(y))} = (1-\alpha) * C\left(A^{Harrod}\right).$$

2. Let *F (A)* denote the five-country measure of *A*:

$$F\left(A^{Hicks}\right) \equiv \frac{\ln\left[\left(\prod_{i=1}^{5} A_i^{Hicks} \Big/ \prod_{j=n-4}^{n} A_j^{Hicks}\right)^{1/5}\right]}{\ln\left[\left(\prod_{i=1}^{5} y_i \Big/ \prod_{j=n-4}^{n} y_j\right)^{1/5}\right]} = \frac{\ln\left[\left(\prod_{i=1}^{5}\left(A_i^{Harrod}\right)^{(1-\alpha)} \Big/ \prod_{j=n-4}^{n}\left(A_j^{Harrod}\right)^{(1-\alpha)}\right)^{1/5}\right]}{\ln\left[\left(\prod_{i=1}^{5} y_i \Big/ \prod_{j=n-4}^{n} y_j\right)^{1/5}\right]}$$

$$= \frac{(1-\alpha)\ln\left[\left(\prod_{i=1}^{5}\left(A_i^{Harrod}\right) \Big/ \prod_{j=n-4}^{n}\left(A_j^{Harrod}\right)\right)^{1/5}\right]}{\ln\left[\left(\prod_{i=1}^{5} y_i \Big/ \prod_{j=n-4}^{n} y_j\right)^{1/5}\right]} = (1-\alpha) * F\left(A^{Harrod}\right)$$

B. Appendix Tables

Table A1 — Basic Data

Country	Output per Worker	Physical Capital per Worker	Human Capital per Worker		Dummies			
	y	k	h	h_Q	*BMS*	*S*	*r*	*QL2**
LUXEMBOURG	1.031	1.242	0.664	0.629	1	1	3	0
U.S.A.	1.000	1.000	1.000	1.000	1	0	1	0
CANADA	0.935	0.993	0.752	0.926	1	0	1	0
SWITZERLAND	0.892	1.256	0.694	0.996	0	0	3	0
BELGIUM	0.863	0.887	0.765	1.009	1	0	1	0
NETHERLANDS	0.850	0.890	0.590	0.697	1	0	1	0
ITALY	0.838	0.949	0.504	0.528	1	0	3	0
FRANCE	0.826	0.978	0.543	0.650	1	0	3	0
AUSTRALIA	0.824	1.011	0.794	1.115	1	0	2	0
GERMANY, WEST	0.803	0.950	0.636	0.664	1	0	3	0
NORWAY	0.795	1.062	0.594	0.870	1	0	1	0
SWEDEN	0.772	0.832	0.740	0.978	1	0	1	0
FINLAND	0.744	1.052	0.751	1.054	1	0	3	0
OMAN	0.732	0.540	0.518	0.450	0	1	3	1
U.K.	0.728	0.599	0.659	0.957	1	0	1	0
AUSTRIA	0.726	0.821	0.551	0.670	1	0	3	0
SPAIN	0.717	0.739	0.573	0.638	1	0	0	0
PUERTO RICO	0.711	0.477	0.875	0.798	0	1	0	1
NEW ZEALAND	0.691	0.879	1.312	2.860	1	0	1	0
ICELAND	0.679	0.760	0.633	0.700	0	0	3	0
DENMARK	0.679	0.796	0.835	1.285	1	0	2	0
SINGAPORE	0.663	0.664	0.313	0.380	0	0	0	0
IRELAND	0.654	0.637	0.644	0.698	1	0	3	0
ISRAEL	0.647	0.560	0.723	0.881	1	0	0	0
SAUDI ARABIA	0.640	0.422	0.518	0.450	0	1	3	1
HONG KONG	0.621	0.361	1.026	2.355	1	0	1	0
JAPAN	0.615	0.785	0.509	0.714	1	0	0	0
TRINIDAD&TOBAGO	0.541	0.420	0.598	0.593	1	0	3	0
MALTA	0.495	0.378	0.570	0.705	0	0	3	0
CYPRUS	0.491	0.440	0.391	0.389	0	0	0	0
GREECE	0.482	0.481	0.642	0.706	1	0	0	0
VENEZUELA	0.474	0.446	0.684	0.567	1	0	0	0
MEXICO	0.463	0.312	0.665	0.529	1	0	0	0
PORTUGAL	0.452	0.352	0.366	0.356	1	0	3	0
KOREA, REP.	0.436	0.331	0.823	1.150	1	0	1	0
SYRIA	0.432	0.261	0.455	0.351	1	0	3	0
U.S.S.R.	0.417	0.630	0.881	1.115	0	0	3	0
BARBADOS	0.400	0.209	0.772	1.098	1	0	3	0
ARGENTINA	0.365	0.359	0.414	0.424	1	0	0	0
JORDAN	0.344	0.228	0.526	0.483	0	0	3	0
MALAYSIA	0.341	0.276	0.627	0.743	1	0	3	0
ALGERIA	0.331	0.324	0.350	0.289	0	0	3	0
IRAQ	0.323	0.314	0.348	0.287	0	0	3	0
CHILE	0.322	0.272	0.359	0.284	1	0	0	0
URUGUAY	0.322	0.253	0.842	0.987	1	0	0	0
FIJI	0.321	0.216	0.829	1.146	0	0	3	0
IRAN	0.310	0.253	0.359	0.265	1	0	0	0

Continued...

Table A1 — Continued

Country	Output per Worker	Physical Capital per Worker	Human Capital per Worker		Dummies			
	y	k	h	h_Q	*BMS*	*S*	*r*	*QL2**
BRAZIL	0.300	0.239	0.774	0.587	1	0	0	0
HUNGARY	0.294	0.389	0.753	1.104	1	0	3	0
MAURITIUS	0.277	0.105	0.651	0.788	1	0	3	0
COLOMBIA	0.275	0.174	0.510	0.434	1	0	0	0
COSTA RICA	0.273	0.192	0.399	0.396	1	0	0	0
YUGOSLAVIA	0.272	0.465	0.270	0.279	1	0	0	0
SOUTH AFRICA	0.261	0.216	0.635	0.704	0	0	0	0
NAMIBIA	0.259	0.269	0.461	0.407	0	1	3	1
SEYCHELLES	0.248	0.154	0.512	0.476	0	1	3	1
ECUADOR	0.246	0.229	0.494	0.431	1	0	0	0
TUNISIA	0.241	0.115	0.361	0.337	1	0	3	0
TURKEY	0.235	0.186	0.376	0.346	1	0	2	0
GABON	0.219	0.231	0.512	0.476	0	1	3	1
YEMEN	0.219	0.077	0.240	0.235	0	1	0	1
PANAMA	0.218	0.192	0.788	0.788	1	0	3	0
CZECHOSLOVAKIA	0.210	0.277	0.924	1.076	0	0	3	1
SURINAME	0.203	0.205	0.553	0.520	1	1	3	1
POLAND	0.203	0.381	1.021	1.826	1	0	3	0
GUATEMALA	0.202	0.083	0.346	0.323	1	0	3	1
REUNION	0.198	0.158	0.512	0.476	0	1	3	1
DOMINICAN REP.	0.188	0.145	0.429	0.386	1	0	3	0
EGYPT	0.187	0.038	0.440	0.324	1	0	3	0
PERU	0.186	0.195	0.588	0.522	1	0	3	0
MOROCCO	0.184	0.072	1.606	1.000	1	1	0	1
THAILAND	0.184	0.095	1.057	1.039	1	0	0	0
BOTSWANA	0.178	0.108	0.652	0.458	1	0	0	0
PARAGUAY	0.174	0.111	0.568	0.494	1	0	0	0
SWAZILAND	0.171	0.094	0.460	0.415	1	0	3	0
SRI LANKA	0.156	0.071	0.683	0.616	1	0	3	0
EL SALVADOR	0.149	0.062	0.380	0.298	1	0	0	0
BOLIVIA	0.145	0.090	0.319	0.273	1	0	0	0
JAMAICA	0.140	0.139	0.484	0.499	1	0	1	0
INDONESIA	0.137	0.099	0.511	0.477	1	0	1	0
DJIBOUTI	0.133	0.069	0.461	0.407	0	1	3	1
BANGLADESH	0.130	0.018	0.353	0.339	1	0	3	1
PHILIPPINES	0.130	0.089	0.516	0.404	1	0	0	0
PAKISTAN	0.126	0.043	0.293	0.286	1	0	0	1
CONGO	0.122	0.046	0.501	0.539	1	0	3	0
HONDURAS	0.121	0.069	0.426	0.328	1	0	0	0
NICARAGUA	0.113	0.089	0.396	0.309	0	0	3	0
ROMANIA	0.112	0.119	0.801	0.829	0	0	3	1
INDIA	0.088	0.045	0.616	0.346	1	0	0	0
IVORY COAST	0.084	0.047	0.461	0.407	1	1	3	1
PAPUA N.GUINEA	0.082	0.068	0.270	0.242	0	0	0	0
GUYANA	0.081	0.149	0.660	0.738	0	0	3	0

Continued...

Table A1 — Continued

Country	Output per Worker	Physical Capital per Worker	Human Capital per Worker		Dummies			
	y	k	h	h_Q	*BMS*	*S*	*r*	*QL2**
CAPE VERDE IS.	0.075	0.070	0.461	0.407	0	1	3	1
CAMEROON	0.068	0.031	0.356	0.340	1	0	3	0
SIERRA LEONE	0.068	0.005	0.283	0.268	1	0	0	1
ZIMBABWE	0.066	0.047	0.282	0.271	1	0	0	0
SENEGAL	0.065	0.014	0.336	0.312	1	0	1	1
SUDAN	0.063	0.041	0.291	0.275	0	0	1	1
NEPAL	0.062	0.016	0.271	0.266	1	0	3	1
CHINA	0.060	0.050	0.664	1.012	0	0	3	0
LIBERIA	0.058	0.033	0.483	0.410	0	0	0	1
NIGERIA	0.057	0.034	0.376	0.343	1	1	0	0
LESOTHO	0.057	0.033	0.309	0.322	0	0	0	0
ZAMBIA	0.056	0.059	0.572	0.464	1	0	2	0
HAITI	0.054	0.018	0.342	0.315	0	0	3	1
BENIN	0.052	0.019	0.296	0.278	1	0	3	1
GHANA	0.051	0.012	0.362	0.288	0	0	0	0
KENYA	0.051	0.028	0.427	0.334	1	0	2	0
GAMBIA	0.047	0.014	0.269	0.258	0	0	3	1
MAURITANIA	0.045	0.037	0.384	0.342	0	1	3	1
SOMALIA	0.045	0.022	0.355	0.322	0	1	0	1
GUINEA	0.043	0.011	0.384	0.342	0	1	3	1
TOGO	0.043	0.029	0.393	0.329	0	0	3	0
MADAGASCAR	0.042	0.004	0.384	0.342	1	1	3	1
MOZAMBIQUE	0.042	0.005	0.260	0.242	0	0	3	0
RWANDA	0.042	0.009	0.310	0.289	1	0	3	1
GUINEA-BISS	0.040	0.028	0.384	0.342	0	1	3	1
ANGOLA	0.040	0.007	0.461	0.407	0	1	3	1
MYANMAR	0.037	0.012	0.347	0.334	0	0	3	1
COMOROS	0.034	0.025	0.384	0.342	0	1	3	1
CENTRAL AFR.R.	0.033	0.010	0.298	0.257	0	0	3	0
MALAWI	0.033	0.013	0.312	0.290	1	0	0	1
CHAD	0.031	0.004	0.384	0.342	0	1	3	1
UGANDA	0.031	0.004	0.556	0.459	0	0	0	1
TANZANIA	0.031	0.013	0.384	0.342	1	1	2	1
ZAIRE	0.030	0.008	0.369	0.318	0	0	3	0
MALI	0.030	0.008	0.261	0.252	1	0	3	1
BURUNDI	0.029	0.007	0.384	0.342	0	1	3	1
BURKINA FASO	0.029	0.011	0.384	0.342	0	1	3	1
NIGER	0.028	0.013	0.248	0.242	0	0	3	1
ETHIOPIA	0.019	0.004	0.353	0.320	1	1	0	1

Notes: Data: United States = 1. — Dummies: *BMS*: 1 = Benchmark Study. *S* and *QL2**: 1 = Imputed.
r: Number of imputed rates of return to education.

Table A2 —Factor Inputs vs. Productivity in the OECD: Five-Country Measure

$$\ln\left(\left(\prod_{i=1}^{5} Z_i \Big/ \prod_{j=n-4}^{n} Z_j\right)^{1/5}\right) \Big/ \ln\left(\left(\prod_{i=1}^{5} y_i \Big/ \prod_{j=n-4}^{n} y_j\right)^{1/5}\right)$$

with n = sample size, countries i, ..., j, ..., n ranked according to y, and Z given in each column

Identifying Productivity Assumption	Harrod-Neutrality		Hicks-Neutrality	
	Factor Inputs X	Productivity A	Factor Inputs X	Productivity A
HJ	0.54	0.46	0.70	0.30
GRW1	0.73	0.27	0.82	0.18
GRW2	0.91	0.09	0.94	0.06

Notes: HJ = Based on *Hall/Jones* methodology to calculate H, with updated data but without mining adjustment. — GRW1 = Based on our measure of H. — GRW2 = Based on our measure of H_Q.