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Development Accounting, the Elasticity of Substitution, and Non-neutral Technological Change

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We apply the tools of development accounting to a broad panel over the period 1970–2014. However, we depart from the traditional Cobb–Douglas hypothesis with Hicks-neutral technological change, and assume a CES technology, which allows for a constant but non-unitary elasticity of substitution, and for non-neutral technological change. For different values of the elasticity of substitution, and different representations of technological change, we find that the cross-country variation in GDP per worker accounted for by factor inputs is decreasing over time until the mid-2000s, when it reverses its trend. In addition, we find that in the recent period technology accounts for up to 80% of the cross-country variation in GDP per worker.

Nós aplicamos as técnicas de contabilidade do desenvolvimento em um amplo painel de países no período 1970–2014. Entretanto, nós desviamos da tradicional hipótese da Cobb–Douglas com progresso tecnológico Hicks-neutro, e assumimos uma tecnologia CES, que permite elasticidade de substituição constante, porém diferente da unidade, e progresso tecnológico não-neutro. Para diferentes valores da elasticidade de substituição, e diferentes representações do progresso tecnológico, nossas estimativas sugerem que a variação no PIB por trabalhador entre países que pode ser explicada pela variação nos fatores de produção é decrescente ao longo do tempo até a metade dos anos 2000s, quando essa tendência é revertida. Adicionalmente, nossas estimativas sugerem que no período recente diferenças na tecnologia entre os países explicam cerca de 80% da variação do PIB per capita entre os países.

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1. INTRODUCTION

The current consensus in the Development Accounting literature establishes that the breakdown technology vs. inputs is "50-50", (see Caselli, 2005, for instance). That is, 50% of the cross-country variance in GDP per worker can be accounted for by cross-country differences in technology, and the remainder 50% can be accounted for by cross-country differences in factor inputs. However, this consensus rests largely on cross-section exercises with the Cobb–Douglas assumption.

In fact, the Cobb–Douglas (CD) production function is the number one choice to represent the aggregate technology in development accounting exercises. In general, one justifies the CD assumption on grounds that its property of constant factor shares matches the data. However, the evidence in Bernanke & Gurkaynak (2001) suggests that labor shares vary substantially across countries. If indeed factor shares vary across countries, then the CD assumption may not be the best representation for the aggregate technology.

In addition to its property of constant factor shares, the CD production function restricts the elasticity of substitution between capital and labor, henceforth denoted by σ, to be constant and equal to one. Whether or not σ is unitary is an empirical question. And, the empirical evidence does not support an unitary σ. For instance, for a panel of 82 countries over the period 1960–1987, Duffy & Papageorgiou (2000) find evidence that σ is well above unity, whereas Mello (2015), for a panel of 100 countries over the period 1970–2008, finds estimates of σ that are below unity. The value of the elasticity of substitution matters for development accounting exercises and, therefore, getting the appropriate value for σ is important.

Another restriction of the CD production function is that differences in technology arise in a neutral, or bias-free, form. This restriction derives from the property of the CD, which is the only production function in which the three forms of technological change—Hicks neutral, Solow neutral, and Harrod neutral—are equivalent. This can be shown as follows. Take a CD with Harrod-neutral (labor-augmenting) technological change: $Y = K^{\alpha}(AhL)^{1-\alpha}$. It is easy to see that this CD is equivalent to a CD with Hicks-neutral technological change, such as this $Y = A^{1-\alpha}K^{\alpha}(hL)^{1-\alpha}$, which is also equivalent to a CD with Solow neutral (capital-augmenting) technological change, $Y = (A^{\frac{1-\alpha}{\alpha}}K)^{\alpha}(hL)^{1-\alpha}$. That is, in the three cases above, technology enters equivalently in a multiplicative form.

One of the implications of this restriction is that if one country is technologically more advanced than another is, then it must use all its factor inputs more efficiently than the other country does. Therefore, a situation in which one country uses capital more efficiently than the other does, while it uses human capital less efficiently, cannot be identified when one assumes a CD production function.

The problem with this is that the evidence suggests that the efficiency with which factor inputs are used varies across countries. According to the evidence in Caselli & Coleman II (2006), rich countries use skilled labor more efficiently than poor countries do, whereas poor countries use unskilled labor more efficiently. Similarly, Caselli (2005) presents evidence that rich countries use human capital more efficiently than poor countries do. In order to identify these differences we need to depart from the CD world.

If indeed the elasticity of substitution differs from unity and factor-efficiency is non-neutral, as the empirical evidence suggests, then performing development accounting exercises relaxing these two constraints may change the consensus view, and, consequently, may change any policy implications derived from the exercise. These two restrictions—unitary elasticity of substitution and factor neutrality—can be relaxed by assuming a Constant Elasticity of Substitution (CES) production function as representative of the aggregate technology. The CES is the simplest production function that allows for a constant but non-unitary elasticity of substitution and non-neutral technological progress.

In this article, we perform a series of development accounting exercises for a broad panel of countries assuming a CES aggregate technology that allows for different values of the elasticity of substitution and factor non-neutrality in technological progress. Additionally, we explore the time variation in the data by applying the tools of development accounting on the time series for GDP per worker from 1970 to 2014, instead of focusing on a specific year as in traditional cross-section studies in the literature.

We construct a panel with data on 84 countries over the period 1970–2014 from the latest version of the PWT, version 9.0. Our estimates suggest that the proportion of the cross-country variability in GDP per worker that can be accounted for by the cross-country variability in factor inputs exhibits a persistent decreasing trend. However, from 2005 towards the end of the sample period, it exhibits a soft increasing trend. In the more recent period, the technology-input breakdown is about "80-20" in favor of technology as the key factor behind the huge observed international variation in GDP per worker. This is a big departure from the "50-50" consensus. Moreover, this finding is robust to different values of the elasticity of substitution, and different representations of technological progress.

Additionally, as a robustness check, we construct two panels with data from PWT 8.1 and PWT 7.0 and apply the same development accounting tools to these panels. Our initial findings are corroborated when we use data from PWT 8.1, and corroborated to a lesser extent when we use data from PWT 7.0. Interestingly, the explanatory power of factors of production as a key determinant of the cross-country variance in GDP per worker is greater when we use data from PWT 9.0 and PWT 8.1.

We contribute to the debate by shedding light on the proximate causes of economic growth. In particular, our study relates to Caselli (2005), Aiyar & Dalgaard (2009), Mello (2009), Ferreira, Pessoa, & Veloso (2008), and Arezki & Cherif (2010). We use the traditional tools of development accounting exercises applied to cross-sectional data, as in Caselli (2005), and apply them on a panel data setting, exploring the time variation in the data as in Mello (2009), Ferreira et al. (2008), and Arezki & Cherif (2010). Moreover, we study the sensitivity of development accounting exercises with respect to the value of the elasticity of substitution in the representative aggregate technology as in Aiyar & Dalgaard (2009), and the effects of non-neutral technological change as in Caselli & Coleman II (2006), and Arezki & Cherif (2010). Additionally, we explore the latest version of Penn World Tables dataset (version 9.0), as well as earlier versions of this dataset (versions 8.1 and 7.0).

We structure this article as follows. In section 2, we briefly review the literature. In section 3, we present our methodology, describing how we can decompose a CES production function into a factor-only component, and a technology component. In section 4, we present our data. In section 5, we present our estimates of the successes measures of the factor-only model for the PWT version 9.0. On section 6, we present estimates of the measures of success of the factor-only model for data from PWT versions 8.1 and 7.0, as a robustness check. Finally, section 7 concludes.

2. RELATED LITERATURE

The debate about the determinants of the huge observed cross-country income differences, whether it is the technology or factor inputs, goes back to the late 1960s (Caselli, 2008). However, it was not until the publication of Klenow & Rodríguez-Clare (1997) that the tools and tricks of development accounting were popularized.

Development accounting is to cross-section data, what growth accounting is to time series data. In a growth accounting exercise one computes, over a period of time, the growth rate of output and factor inputs, and estimate the growth in total factor productivity (TFP) as a residual. The exercise is helpful to identify the sources of growth, whether it comes from inputs or TFP. If growth in output comes from inputs, then it is likely to be temporary, whereas if it comes from TFP then it can be long lasting.

In a development accounting exercise, one has a cross-section of countries, and performs the decomposition of the level of GDP per worker into factor inputs and technology (TFP). Then one examines to what extent the cross-country variability in factor inputs vis-à-vis variability in TFP can explain the cross-country variability in GDP per worker.

The decomposition exercise can give insight into the proximate causes of growth. By identifying the sources of cross-country variability in GDP per worker one can think about policies aimed at reducing inequality among nations. For instance, if one finds that the quantity of factor inputs can account for a large portion of the cross-country variability in output per worker, then, instead of focusing on technology, policy makers should look into the causes of low accumulation of factor inputs across countries.

Caselli (2005), the most cited survey in the literature, performs a series of development accounting exercises for a cross-section of 94 countries in the year 1996 with data from Penn World Tables version 6.1. His estimates suggest the breakdown factor inputs versus technology is about "50-50". According to Hsieh & Klenow (2010), another recent survey, the current consensus establishes that technology accounts for 50-70% of the cross-country differences in GDP per worker.

In our decomposition exercise, we break down GDP per worker in terms of the capital-output ratio, as in Klenow & Rodríguez-Clare (1997), among others. Moreover, to assess the role of factor inputs vis-à-vis technology in accounting for cross-country output differences, we use the methodology in Caselli (2005). Furthermore, we follow Mello (2009), Ferreira et al. (2008), and Arezki & Cherif (2010) in constructing a panel and exploring the time variation in the data, instead of looking at a single point in time as in much of the literature.

3. METHODOLOGY

We represent the aggregate technology by a CES production function as follows:

$$Y = \left(\alpha K^{\frac{\sigma-1}{\sigma}} + (1-\alpha)(AhL)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}, \tag{1}$$

where Y is output, K is physical capital, A is Harrod-neutral (labor-augmenting) technological progress, h is human capital per worker, and L is the number of workers. The elasticity of substitution given by the parameter σ. If $\sigma = 1$ we are back to the Cobb–Douglas world, in which output is given by $Y = K^{\alpha}(AhL)^{1-\alpha}$. Aiyar & Dalgaard (2009) also adopt the above functional form.

Based on the production function in (1), we can break down output per worker into two components, a factor-only component, and a technology component:

$$\frac{Y}{L} = \left(\frac{1-\alpha}{1-\alpha(K/Y)^{\frac{\sigma-1}{\sigma}}}\right)^{\frac{\sigma}{\sigma-1}} Ah. \tag{2}$$

In this case, the factor-only model is given by

$$y_{\mathrm{KH}} = \left(\frac{1-\alpha}{1-\alpha(K/Y)^{\frac{\sigma-1}{\sigma}}}\right)^{\frac{\sigma}{\sigma-1}}. \tag{3}$$

In the CD case, i.e., if $\sigma = 1$, the factor-only model is given by

$$y_{\mathrm{KH}} = \left(\frac{K}{Y}\right)^{\frac{\alpha}{1-\alpha}} h. \tag{4}$$

Equation (4) is the well-known Klenow & Rodríguez-Clare (1997) break-down.

The specification in (1) assumes that technological change is Harrod-neutral or labor augmenting. However, we can extend this specification to include non-neutral technological change. Following Aiyar & Dalgaard (2009), we assume a CES that allows for Harrod (labor) and Solow (capital) neutral technological change:

$$Y = \left(\alpha(BK)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)(AhL)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}, \tag{5}$$

where B denotes the Solow neutral (capital augmenting) technological change, and A denotes the Harrod-neutral (labor augmenting) technological change. We can rearrange equation (5) and break it down into two components, just like we did with equation (1). We obtain the following expression:

$$\frac{Y}{L} = \left(\frac{1-\alpha}{1-\alpha\left[B(K/Y)\right]^{\frac{\sigma-1}{\sigma}}} \right)^{\frac{\sigma}{\sigma-1}} Ah. \tag{6}$$

The problem with the above decomposition is that the capital augmenting parameter B is included in the factor-only component. That is, in practice, we have not separated the technology component from the factor-only component. In order to obtain a feasible decomposition based on equation (6), we need to find a way to estimate or "fix" the capital augmenting parameter B.

We follow the strategy in Caselli & Coleman II (2006), which is also adopted by Aiyar & Dalgaard (2009). The idea is, first, to fix the parameter B at the "technological frontier", which is taken to be the U.S. level. Second, given competitive markets and the production function in equation (5), we can write the capital share as follows:

$$S_k = \alpha B^{\frac{\sigma-1}{\sigma}} (K/Y)^{\frac{\sigma-1}{\sigma}}, \tag{7}$$

where S_k denotes the capital share. The trick here is to assume that all countries have access to the technological frontier. That is, all countries have access to the same (U.S.) parameter B. From equation (7), we can estimate the parameter B as follows:

$$\alpha B^{\frac{\sigma-1}{\sigma}} = S_K^{\mathrm{US}} \left(\frac{Y^{\mathrm{US}}}{K^{\mathrm{US}}} \right)^{\frac{\sigma-1}{\sigma}}, \tag{8}$$

where the variables with the superscript denote their U.S. levels. Implementing this strategy, when technological change is both Harrod and Solow neutral, the factor-only model, denoted by $y_{\mathrm{KH}}^{\mathrm{AB}}$, is given by:

$$y_{\mathrm{KH}}^{\mathrm{AB}} = \left(\frac{1-\alpha}{1 - S_K^{\mathrm{US}} \left(\frac{Y^{\mathrm{US}}}{K^{\mathrm{US}}} \right)^{\frac{\sigma-1}{\sigma}} \left(\frac{K}{Y} \right)^{\frac{\sigma-1}{\sigma}}} \right)^{\frac{\sigma}{\sigma-1}} h. \tag{9}$$

With the exception of the non-observable parameter B, which we estimate with equation (8), all other variables in equation (9) can be directly obtained from PWT dataset, or can be constructed from the variables therein.

The first measure of success of the factor-only model we look at is the ratio of the variance of the log of the factor-only model to the variance of the log of GDP per worker. We denote this measure of success by $\mathrm{S1}$:

$$\mathrm{S1} = \frac{\mathrm{Var}\left(\mathrm{Log}(y_{\mathrm{KH}})\right)}{\mathrm{Var}\left(\mathrm{Log}(y)\right)}. \tag{10}$$

As correctly pointed out in Caselli (2005), the $\mathrm{S1}$ measure is sensitive to extreme values, which may contaminate the analysis. In this sense, Caselli (2005) also considers a second measure of success, denoted by $\mathrm{S2}$, which takes the ratio of the 90^{th} to 10^{th} percentile ratio of the factor-only model to the 90^{th} to 10^{th} percentile of the observed GDP per worker. The $\mathrm{S2}$ measure is given by

$$\mathrm{S2} = \frac{y_{\mathrm{KH}}^{90\mathrm{th}} / y_{\mathrm{KH}}^{10\mathrm{th}}}{Y^{90\mathrm{th}} / Y^{10\mathrm{th}}}, \tag{11}$$

where $y_{\mathrm{KH}}^{90\mathrm{th}}$ and $y_{\mathrm{KH}}^{10\mathrm{th}}$ denote, respectively, the level of GDP per worker of the factor-only model at the 90^{th} and the 10^{th} percentile, and $Y^{90\mathrm{th}}$ and $Y^{10\mathrm{th}}$ denote the observed level of GDP per worker at the 90^{th} and 10^{th} percentile, respectively.

4. DATA

We construct our main panel with data from the latest version of Penn World Tables (PWT) dataset version 9.0. Our panel includes 84 countries for which population is equal to or greater than 1 million in 1985, and the time series for the variables we use are complete over the period 1970–2014.

Our measure of output is the variable $RGDPO$ (output-side real GDP at chained PPP in millions of 2005 USD), the measure for the aggregate stock of capital is the variable CK (capital stock at PPP in millions of 2005 USD), and the measure of workers is the variable EMP (number of individuals engaged in production). GDP per worker is calculated as the ratio of $RGDPO/EMP$, and the capital-output ratio is computed as $CK/RGDPO$.

Our measure of human capital is the variable hc in PWT 9.0, which is an index of human capital per person, based on years of schooling, from Barro & Lee (2010) dataset, and returns to education, from Psacharopoulos (1994). This measure of human capital is also used in the PWT 8.1.

In addition to the PWT version 9.0, as a robustness check, we work with two other versions of PWT, versions 8.1 and 7.0. For the PWT 8.1, our panel includes 77 countries for which population is greater than or equal to 1 million in 1985, and the time series for the variables is complete over the period 1970–2011.

For the PWT 7.0, we construct a panel with 85 countries for the period 1970–2008. For this panel, we compute the number of workers as $RGDPCH*POP/RGDPWOK$, where we denote the variables by their PWT 7.0 codes. Real GDP (Y) is constructed by multiplying the series $RGDPWOK2$ by the number of workers. The series $RGDPWOK2$ is given by $RGDPL2WOK = RGDPL2*POP/Workers$, where $RGDPL2$ is an updated version of $RGDPL$ which is real GDP (Laspeyre index).

In order to construct the time series for the physical capital stock, we follow Mello (2009) and use the perpetual inventory method. The initial value of aggregate capital is set at $I_0/(g+\delta)$, where I_0 is initial investment (measured as the investment in the first year for which data is available), g is the average growth rate in investment for the first year for which data is available until 1970, and δ is the depreciation rate which we set at 6%. Given K_0, K_t evolves according to the capital accumulation equation, namely, $K_t = (1-\delta)K_{t-1} + I_t$. To ensure the quality of capital stock estimates, we initiate the series on the first year for which data is available and discard all observations until 1969. By discarding the initial years, we guard ourselves against a bad initial guess. See Mello (2009) for more details.

Our measure of human capital for the PWT 7.0, uses the average years of schooling for the population 25 years old or older obtained from Barro & Lee (2010) dataset. Specifically, we assume that human capital H is given by $H = e^{0.1*u}L$, where u is the average years of schooling and L is the number of workers. That is, we assume that the Mincerian coefficient of returns to education is 0.1 for all countries.

In the Appendix, we provide the complete list of countries in the three panels that we use, PWT 9.0, PWT 8.1, and PWT 7.0, as well as the list of countries considered rich/poor, as defined in the next section. Our dataset is available upon request.

5. ESTIMATES

We initially analyze estimates of the $S1$ measure for the case in which technological change is Harrod neutral only. We assume different values for the elasticity of substitution according to the empirical evidence. The exercises are performed for $\sigma = 1.5$, according to the evidence in Duffy & Papageorgiou (2000), for $\sigma = 0.8$ according to the evidence in Mello (2015), and Aiyar & Dalgaard (2009), for $\sigma = 0.5$ according to Antràs (2004), and as a benchmark for $\sigma = 1$, which is the Cobb–Douglas case.[1]

Figure 1 displays the $S1$ measure for a CES with Harrod neutral technological change for data from PWT 9.0. It contains at least four salient features. First, we observe that the higher the elasticity

[1] Antràs's (2004) estimate is for the U.S. economy only.

of substitution the higher the explanatory power of the factor-only model. In particular, the explanatory power of the factor-only model with $\sigma = 1.5$ is about twenty percentage points higher than with $\sigma = 0.5$. Second, for values of the elasticity of substitution equal to or less than one, the factor-only model explains a much lower percentage than the 50% consensus. For instance, for $\sigma = 0.80$, the factor-only model explains about 30% of the cross-country variation in GDP per worker in the mid-1970s, and it decreases to about 10% in the mid-1990s. Only if we assume that $\sigma = 1.5$, that the $S1$ measure comes close to the 50% consensus, but it still trails below the 50% for most of the sample period.

Third, the explanatory power of the factor-only model decreases over time. For instance, in 1970, for $\sigma \leq 1$, the factor-only model explains about 35% of the cross-country variation in GDP per worker. Moreover, in 2000, for $\sigma \leq 1$, its explanatory power drops to less than 20%. For $\sigma = 1.5$, the explanatory power of the factor-only model drops by about 20 percentage points over the period 1970–2005. This finding is consistent with the estimates in Ferreira et al. (2008), and Arezki & Cherif (2010), who also find that the explanatory power of the factor-only is decreasing over time. Fourth, in the last eight years of the sample period, 2006–2014, the explanatory power of the factor-only model increases somewhat. For example, in the case of $\sigma = 1.5$, it increases by more than 10 percentage points, while for $\sigma = 1$ it increases by a few percentage points.

The observations above are confirmed by examining the $S2$ measure of success. As can be seen in Figure 2, the pattern of $S2$ mimics that of $S1$, so that the four observations we made about $S1$ in Figure 1 also apply to $S2$ in Figure 2. One noticeable difference is that, for the entire sample period, according to

Figure 1. Sucess 1 – PWT 9.0.

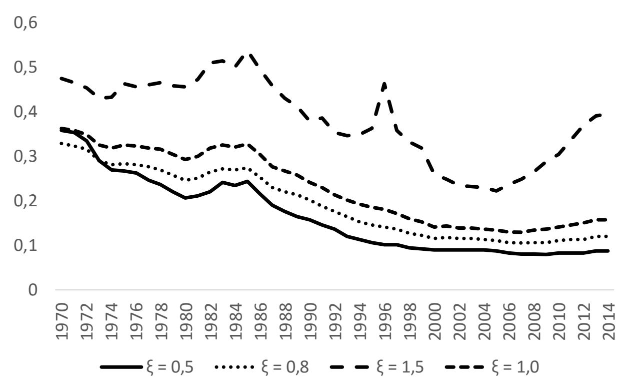


Figure 2. Sucess 2 – PWT 9.0.

the $S2$ measure, the explanatory power of the factor-only model is, on average, five percentage points greater than compared to the $S1$ measure.

In order to learn more about the cross-country variability in GDP per worker, we segment the sample in three parts: rich, middle-income, and poor countries. We consider rich the 21 countries (top 25%) in our panel with the highest level of GDP per worker in the year 2000. The list of rich countries can be found in Table A-1 in the Appendix. Figure 3 displays the $S1$ for measure for the sub-sample of rich countries.

We only report the $S1$ measure for rich countries for $\sigma \leq 1$, because $S1$ estimates for $\sigma = 1.5$ generate too much variability, well above the observed variability in the data. For instance, in the year 1991, the variability generated by the $S1$ measure for $\sigma = 1.5$ is a factor of 12 of the observed variability in observed GDP per worker. In order to avoid any distortion in the figure with such large realizations we omit the $S1$ estimates for $\sigma = 1.5$. These estimates are available upon request.

The $S1$ measure for $\sigma = 0.8$ and $\sigma = 1$, as shown in Figure 3, generates more variability than what is observed in the data for most of the sample period. In particular, for $\sigma = 0.8$ the factor-only model fully accounts for the variability in the data until 2002, and for $\sigma = 1$, until 2003. For $\sigma = 0.5$, the $S1$ measure practically explains all of the variability in the data from 1978 to 2000. Interestingly, starting in the early 2000s, the $S1$ measure for rich countries for any value of σ loses explanatory power fast, reaching 2014 in the range 10%–24%.

The finding that the factor-only model has a higher explanatory power for rich countries is intuitive. After all, for rich countries the observed cross-sectional variance of GDP per worker must be smaller than for the panel as a whole. Additionally, it is plausible to assume that rich countries have access to same technology, and, if so, then cross-sectional differences in GDP per worker must come from cross-sectional differences in factor inputs.

If indeed the source of the cross-sectional differences in GDP per worker are cross-sectional differences in factor inputs, then it is easier for the policy maker to design policies to reduce income inequality. The reason being is that differences in technology can come from many sources, such as credit market imperfections or judicial uncertainty, while differences in factor inputs can be reduced via accumulation of capital, with a high investment rate.

Figure 4 displays the $S2$ measure for rich countries, including $S2$ estimates for $\sigma = 1.5$. The explanatory power of the factor-only model is greater for $\sigma = 1.5$. The range of $S2$ estimates for $\sigma = 1.5$ goes from 1.04 to 2.75, while the range of $S1$ for rich countries, for $\sigma = 1.5$, goes from 1.47 to 13.2, which suggests that the $S1$ measure is in fact contaminated with extreme values and a higher elasticity of substitution magnifies the effects of outliers. Other than that, the general pattern exhibited by the $S2$ measure in Figure 4 for $\sigma \leq 1$ mimics the pattern we observe for the $S1$ measure in Figure 3.

As in the case for the panel as a whole, the explanatory power of $S2$ decreases over time. However, until 2001 it generates enough variability to match the data. Interestingly, the loss in explanatory power is small and it only occurs for $\sigma \leq 1$. In general, we can say that the factor-only model accounts well for the cross-sectional variability in GDP per worker for rich countries.

Figures 5 and 6 display the $S1$ and $S2$ measures for poor countries, respectively. We classify as poor countries the bottom 21 countries (25% of the panel) ranked according to their GDP per worker in year 2000. The list of countries classified as poor is in the Appendix.

Figure 5 displays the $S1$ measure for poor countries. Again, we omit from the $S1$ estimates for $\sigma = 1.5$ due to extreme values. The estimates in Figure 5 show a hump-shaped form, with the hump formed between 1985 and 2000. For the years 1970–1984, the $S1$ estimates fall in the range 35%–60%, and increase over time. In the second period, 1985–2000, for $\sigma = 1$, $S1$ increases and even goes above 1; for $\sigma = 0.8$, $S1$ estimates hover around 60%; and for $\sigma = 0.5$, $S1$ estimates decreases below 40%. For the end of the sample period, 2001–2014, $S1$ estimates decrease fast, reaching low 10s% and 20s%, just to increase slightly in the final three years of the sample period.

Figure 3. Sucess 1 – Rich, PWT 9.0.

Figure 4. Sucess 2 – Rich, PWT 9.0.

Figure 6 displays the estimates of S2 for poor countries, excluding estimates for $\sigma = 1.5$. Again, S2 estimates for $\sigma = 1.5$ exhibit a lot of variability, being above one for most of the sample period, 1981–2005. For other values of the elasticity of substitution, the pattern we observe in Figure 6 is consistent with the one in Figure 5. That is, for $\sigma \leq 1$, we observe a hump-shaped form, with the hump between the years 1985–2000. Additionally, the range of estimates is similar to the range of estimates in Figure 5, with the explanatory power of the factor-only model oscillating around 50% in the beginning of the sample period, reaching 100% for $\sigma = 1$ around 1990, and settling at 35%–45% at the end of the sample period.

Based on figures 5 and 6, we conclude that the factor-only model, for $\sigma \leq 1$, accounts for 35%–45% for the cross-country variation in GDP per worker, and for $\sigma = 1.5$, it accounts for 50%–70%. That is, the elasticity of substitution does affect the explanatory power of the factor-only model. However, it does not lead it too far off from the "50-50" consensus.

Figure 7 displays S1 estimates for the case in which technological progress is non-neutral, that is, it is Harrod and Solow neutral. Estimates of S1 for $\sigma = 0.5$ and $\sigma = 0.8$, in Figure 7, exhibit a decreasing trend, starting in the low 40s% and falling in the range of 10s% and 20s% towards the end of the sample period. Estimates of S1, for $\sigma = 1.5$, also exhibit a decreasing trend. However, it starts in the low 20s% and reach the 10% around year 2000, when it starts to increase towards 15%. Additionally, for most of the sample period the explanatory power of the factor-only model is greater when $\sigma = 0.8$. This is

Figure 5. Sucess 1 – Poor, PWT 9.0.

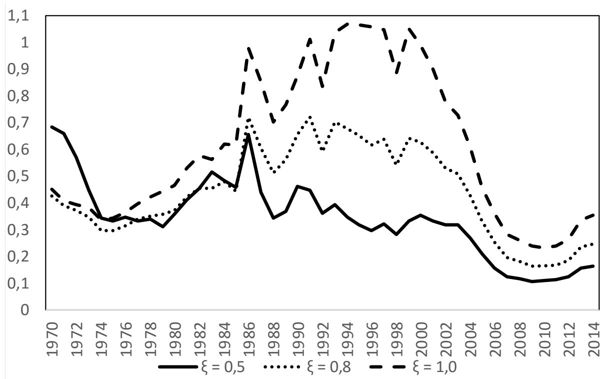
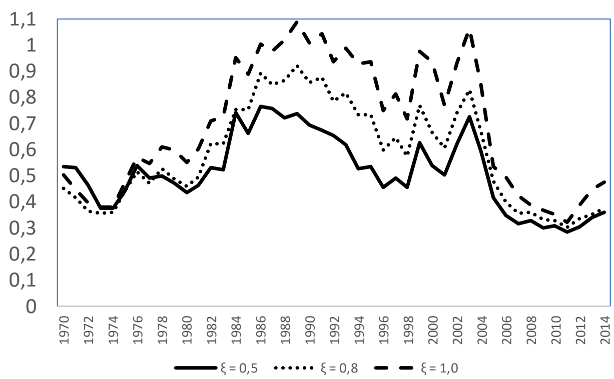


Figure 6. Sucess 2 – Poor, PWT 9.0.



in sharp contrast with the Harrod neutral only case, in which the explanatory power of the factor-only model is greater with $\sigma = 1.5$. Moreover, the $S1$ estimates intersect at several points, suggesting that $S1$ is not monotonic with respect to the elasticity of substitution.

The $S2$ measure for the Harrod and Solow neutral case, shown in Figure 8, mimics the pattern seen in Figure 7. As before, the explanatory power of the factor-only model is decreasing over time, and it is greatest when $\sigma = 0.8$. More specifically, the explanatory power of the factor-only model starts in the range 30%–50%, and decreases over time to the range 10%–20%. The fall in the explanatory power of the factor-only model starts in the mid-1980s and it continues until the year 2000, just to increase slightly until 2014 and finish it around 15%.

Recall that to compute the $S1$ measure for the case of Harrod and Solow neutral technological change, we assume that all countries have access to the U.S. capital augmenting technology. Note, however, that countries still differ in their labor augmenting technological change. Therefore, all the cross-country variability in technology comes from the cross-sectional variability in labor-augmenting technology. Thus, the decreasing explanatory power of the factor-only model is exactly matched by a larger role of cross-country differences in labor augmenting technology in accounting for cross-country income differences.

The picture that emerges from the above estimates is that the "50-50" consensus seems to be valid until the late 1980s or early 1990s. However, currently, the estimates suggest that the bulk of

Figure 7. Sucess 1 – non-neutral Tech. Progress, PWT 9.0.

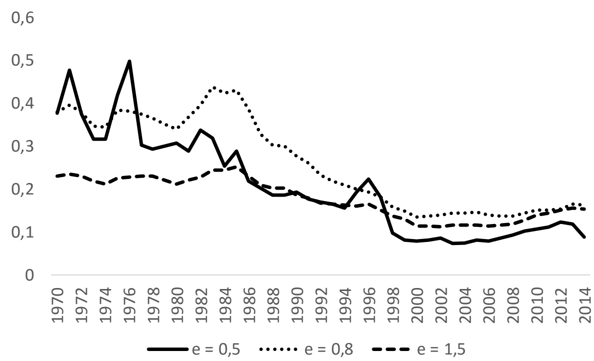
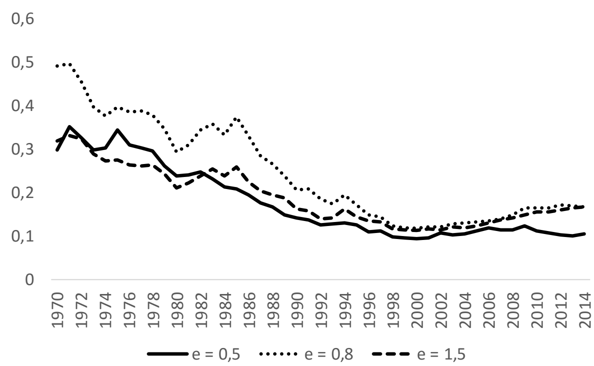


Figure 8. Sucess 2 – non-neutral Tech. Progress, PWT 9.0.



cross-country differences in GDP per worker are due to cross-country differences in the efficiency with which inputs are used. In particular, our estimates suggest that the current breakdown is "80-20" in favor of technology. These findings seem to be robust with respect to the different values of the elasticity of substitution and the form of technological change.

Any policy prescription aimed at reducing cross-country income differences should focus on the ability to convert inputs into output, that is, on efficiency, rather than on fostering the accumulation of inputs.

6. ROBUSTNESS CHECK

In this section, we check for robustness of our estimates by computing the $S1$ and $S2$ measures for previous versions of the PWT dataset, namely, versions 8.1 and 7.0. We omit some of the figures here to economize on space (they are available upon request). We construct the panels using the same criteria as in section 4, that is, by selecting countries for which the population in 1985 is above 1 million, and data was available for the entire sample period, 1970–2011 for PWT 8.1, and 1970–2008 for PWT 7.0.

Figure 9 displays the $S1$ measure for the PWT 8.1. First, the higher the elasticity of substitution the higher the explanatory power of the factor-only model. In particular, the explanatory power of the factor-only model with $\sigma = 1.5$ is about 20 percentage points higher than with $\sigma = 0.5$. Second, for values of the elasticity of substitution equal or less than one, the factor-only model explains a much lower percentage than the 50% consensus. For instance, for $\sigma = 0.80$, the factor-only model explains

Figure 9. Sucess 1 – PWT 8.1.

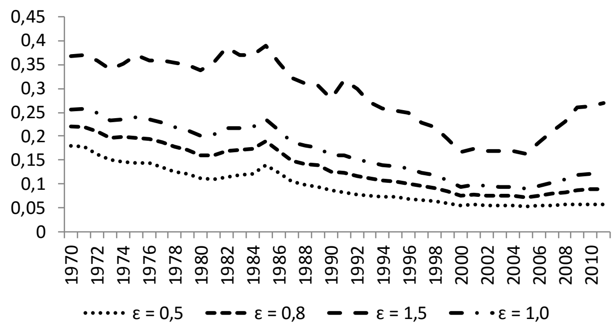
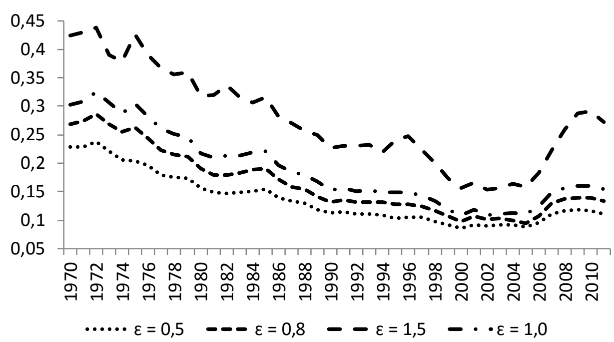


Figure 10. Sucess 2 – PWT 8.1.



about 30% of the cross-country variation in income per worker in the mid-1970s and it decreases to about 10% in the mid-1990s. Only if we assume that $\sigma = 1.5$, that the S1 measure comes closer to the 50% consensus, but it still trails below the 50% for most of the sample period. Lastly, estimates in Figure 9 are consistent with the ones we obtain with data from PWT 9.0.

We confirm the above observations by examining the S2 measure of success for PWT 8.1, as shown in Figure 10. The pattern of S2 over time mimics that of S1. Therefore, the same observations we made for Figure 9 are also valid for Figure 10. One noticeable difference is that according to the S2 measure, the explanatory power of the factor-only model averages about five percentage points higher than compared with the S1 measure.

Figures 11 and 12 display, respectively, S1 and S2 estimates assuming a CES with non-neutral technological change, and using data from PWT 8.1. The overall pattern of S1 in Figure 11 is consistent with the one in Figure 7. However, the explanatory power of the factor-only model is substantially reduced when compared to Figure 7, which was constructed using data from PWT 9.0.

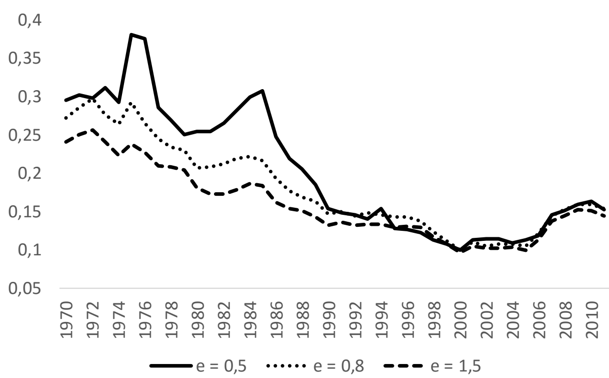
Probably the most interesting aspects in figures 11 and 12 are the decreasing trend in S1 and the end of period kick back. These two aspects that are also present in estimates from PWT 9.0.

As mentioned above, we do not present all the corresponding figures for S1 and S2 constructed with data from PWT 7.0. Below, we present some of the estimates from PWT 7.0, comparing them with estimates from the more recent versions of the PWT.

Assuming Harrod neutral technological change only, Figure 13 displays S2 estimates for $\sigma = 0.8$ for three versions of the PWT we work with. As can be seen in Figure 13, in all cases the explanatory power of the factor-only model decreases over time until 2005, when it shows a soft tendency to in-

Figure 11. Sucess 1 – non-neutral Tech. Progress, PWT 8.1.

Figure 12. Sucess 2 – non-neutral Tech. Progress, PWT 8.1.



crease. Interestingly, the explanatory power of the factor-only model is quite low when we use data from PWT 7.0. The explanatory power of the factor-only model is greater with data from PWT 9.0, although from the mid-1990s towards the end of the sample period the S2 measure has more or less the same value whether computed with data from PWT 9.0 or PWT 8.1. These observations are also true for S2 estimates for $\sigma = 1.5$ assuming Harrod neutral technological change as shown in Figure 14.

We also compute the S2 measure, constructed assuming Harrod and Solow neutral technological change, using data from the three versions of the PWT we work with. Figure 15 displays S2 estimates for $\sigma = 0.8$. The decreasing trend in S2 is present in all cases, less pronounced when we use data from PWT 7.0, but very strong when we use data from PWT 9.0 and 8.1. Again, the explanatory power of the factor-only model is greater when we use data from PWT 9.0. Interestingly, around 1995 we observe a convergence in S2 for data from PWT 9.0 and 8.1, with the explanatory power of the factor-only oscillating between 10% and 15%. Furthermore, we observe the increase in the explanatory power of the factor-only from 2005. These observations are also valid for Figure 16, which displays estimates of S2 assuming Harrod and Solow neutral technological change and $\sigma = 1.5$. We should only add that for $\sigma = 1.5$, the explanatory power of the factor-only model is some 20 percentage points lower than when $\sigma = 0.8$.

Figure 13. Comparing S2 Broad panel ES $= 0.8$.

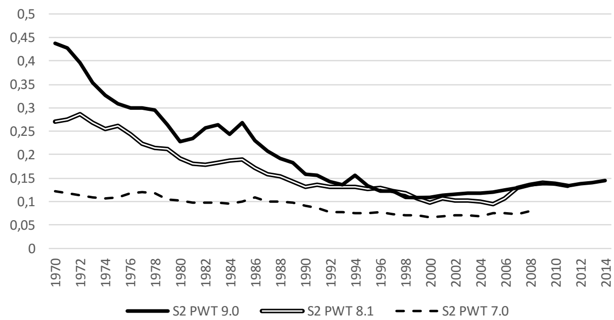
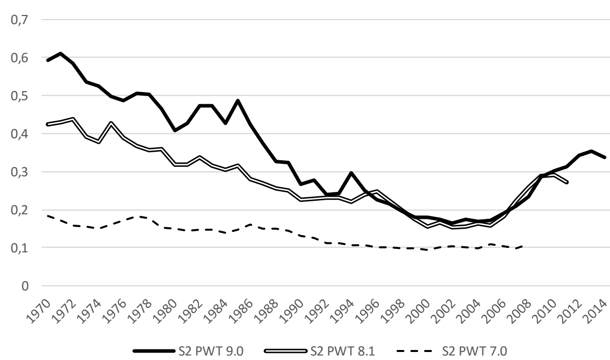


Figure 14. Comparing S2 Broad panel ES $= 1.5$.



7. CONCLUSION

We construct a broad panel with 84 countries over the period 1970–2014 with data from the latest version of PWT 9.0, and apply the tools of development accounting. We depart from two traditional assumptions commonly employed in the literature, namely, the Cobb–Douglas assumption and neutral technological change.

We adopt a CES production function that allows for a constant but non-unitary elasticity of substitution and non-neutral technological change. Our estimates suggest that the explanatory power of the factor-only model exhibits a decreasing trend, with a soft kick back from 2005 to 2014. Additionally, when technological change is Harrod neutral the explanatory power of the factor-only model is greater for $\sigma = 1.5$, whereas when technological change is non-neutral the factor-only model explains more for $\sigma = 0.8$ for PWT 9.0 data, and for $\sigma = 0.5$ for PWT 8.1 data.

Finally, and perhaps most importantly, we find that in the more recent period, the 2000s, cross-country differences in technology can account for up to 80% of the cross-country variation in GDP per worker. This suggests that countries should be primarily concerned with the efficiency in which their factor inputs are used, rather than the accumulation of factor inputs.

Figure 15. Comparing S2 ES = 0.8 Non-neutral T.Ch. – PWT 9.0, 8.1, 7.0.

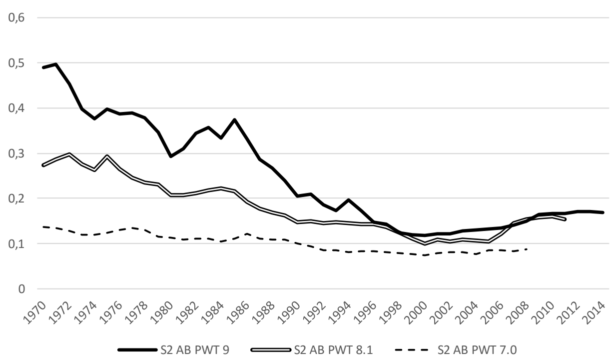
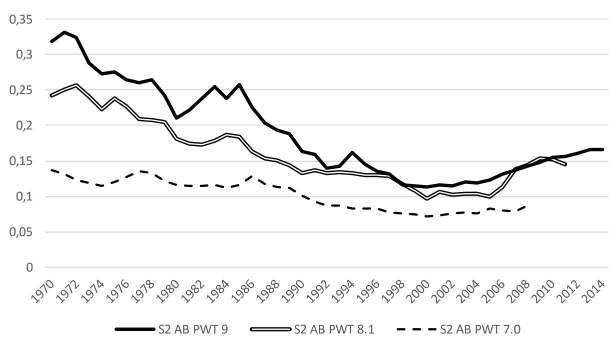


Figure 16. Comparing S2 ES = 1.5 Non-neutral T.Ch. – PWT 9.0, 8.1, 7.0.



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APPENDIX. LISTS AND TABLES

Country List (All countries, $n = 84$, PWT *9.0*)

Albania, Algeria, Angola, Argentina, Australia, Austria, Bangladesh, Belgium, Bolivia, Brazil, Bulgaria, Burkina Faso, Cambodia, Cameroon, Canada, Chile, China, Hong Kong, Colombia, Ivory Coast, Democratic Republic of Congo, Denmark, Domenica Republic, Ecuador, Ethiopia, Finland, France, Germany, Ghana, Greece, Guatemala, Haiti, Honduras, Hungary, India, Indonesia, Iran, Iraq, Ireland, Israel, Italy, Japan, Kenya, Madagascar, Malawi, Malaysia, Mali, Mexico, Morocco, Mozambique, Netherlands, New Zealand, Niger, Nigeria, Norway, Pakistan, Paraguay, Peru, Philippines, Poland, Portugal, South Korea, Romania, Saudi Arabia, Senegal, Singapore, South Africa, Spain, Sri Lanka, Sweden, Switzerland, Syria, Taiwan, Thailand, Tunisia, Turkey, Tanzania, Uganda, United Kingdom, Tanzania, United States, Uruguay, Venezuela, Vietnam, and Zambia.

Table A-1. List of Rich and Poor countries, PWT 9.0.

Rich Countries	GDP per Worker in 2000	Poor Countries	GDP per Worker in 2000
Norway	85,071.2	Syria	5,942.20
United States	81,328.2	Angola	5,827.61
Italy	73,951.2	Haiti	5,497.27
Ireland	73,301.9	Ivory Coast	5,475.58
Australia	68,239.6	Kenya	5,332.06
Canada	68,049.7	India	5,315.27
France	67,944.4	Bangladesh	4,635.60
Austria	67,281.7	Vietnam	4,402.62
Belgium	67,119.2	Zambia	4,216.97
Sweden	66,848.6	Mali	3,281.81
Taiwan	66,290.8	Uganda	3,108.49
U. Kingdom	64,883.0	Nigeria	3,047.78
Finland	64,453.3	Burkina Faso	3,033.20
Netherlands	64,227.3	Tanzania	2,846.06
Switzerland	63,233.0	Cambodia	2,677.09
Israel	63,046.6	Madagascar	2,459.04
Singapore	62,459.8	Malawi	2,351.26
Hong Kong	61,449.7	Niger	2,007.71
Denmark	60,409.8	D. R. of Congo	1,554.43
Japan	59,349.3	Mozambique	1,493.13
Germany	59,240.8	Ethiopia	1,322.92

Country List (All countries, $n = 77$, PWT *8.1*)

Albania, Argentina, Australia, Austria, Bangladesh, Belgium, Bolivia, Brazil, Bulgaria, Cambodia, Cameroon, Canada, Chile, China, Hong Kong, Colombia, Ivory Coast, Democratic Republic of Congo, Denmark, Ecuador, Finland, France, Germany, Ghana, Greece, Guatemala, Honduras, Hungary, India, Indonesia, Iran, Iraq, Ireland, Israel, Italy, Japan, Kenya, Malawi, Malaysia, Mali, Mexico, Morocco, Mozambique, Netherlands, New Zealand, Niger, Norway, Pakistan, Paraguay, Peru, Philippines, Poland, Portugal, South Korea, Romania, Saudi Arabia, Senegal, Singapore, South Africa, Spain, Sri Lanka, Sweden, Switzerland, Syria, Taiwan, Thailand, Tunisia, Turkey, Uganda, United Kingdom, Tanzania, United States, Uruguay, Venezuela, Vietnam, and Zambia.

Table A-2. List of Rich and Poor countries, PWT 8.1.

Rich Countries	GDP per Worker in 2000	**Poor Countries**	GDP per Worker in 2000
Norway	85,071.2	Syria	5,115.6
United States	81,328.2	India	5,090.2
Ireland	73,951.2	Ghana	5,027.7
Italy	73,301.9	Cameroon	4,972.0
Hong Kong	68,239.6	Ivory Coast	4,582.3
Belgium	68,049.7	Senegal	4,503.1
Canada	67,944.4	Bangladesh	4,322.0
Australia	67,281.7	Kenya	4,035.53
Austria	67,119.2	Vietnam	4,026.9
France	66,848.6	Mali	2,992.0
Taiwan	66,290.8	Cambodia	2,688.7
Finland	64,883.0	Zambia	2,420.0
Israel	64,453.3	Uganda	2,281.8
Sweden	64,227.3	Niger	1,986.9
Netherlands	63,233.0	Malawi	1,622.6
U. Kingdom	63,046.6	Tanzania	1,605.0
Switzerland	62,459.8	Mozambique	1,002.9
Singapore	61,449.7	D. R. of Congo	782.4
Denmark	60,409.8		
Germany	59,349.3		
Japan	59,240.8		
Spain	57,689.3		
New Zealand	48,735.8		
South Korea	43,848.7		

Country List (All countries, $n = 86$, PWT *7.0*)

Algeria, Argentina, Australia, Austria, Bangladesh, Benin, Belgium, Bolivia, Brazil, Burundi, Cameroon, Canada, Central Africa Republic, Chile, China, Hong Kong, Colombia, Ivory Coast, Democratic Republic of Congo, Dominican Republic, Denmark, Ecuador, Egypt, El Salvador, Ethiopia, Finland, France, Ghana, Greece, Guatemala, Haiti, Honduras, Hungary, India, Indonesia, Iran, Ireland, Israel, Italy, Jamaica, Japan, Kenya, Madagascar, Malawi, Malaysia, Mali, Mexico, Morocco, Mozambique, Nepal, Netherlands, New Zealand, Niger, Norway, Pakistan, Papua New Guinea, Paraguay, Peru, Philippines, Portugal, Sierra Leone, South Korea, Romania, Rwanda, Senegal, Singapore, South Africa, Spain, Sri Lanka, Sweden, Switzerland, Syria, Taiwan, Thailand, Togo, Tunisia, Turkey, Uganda, United Kingdom, Tanzania, United States, Uruguay, Venezuela, Zambia, and Zimbabwe.