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Accounting for Cross-Country Output Differences: A Sectoral CES Perspective

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Abstract

Conventional development accounting attributes the enormous variation in output per worker across countries to differences in production factors and productivity. Our paper contributes to this literature along three important lines. First, we tackle the simplifying assumption of an aggregate Cobb-Douglas production function by estimating more flexible constant elasticity of substitution (CES) production functions in a tradable market sector and five subsectors across 38 countries. Our results suggest that physical and human capital are gross complements in production in all sectors, indicating that production factors play a larger role in explaining cross-country output differences than previously thought. Second, we find that differences in output per worker largely stem from the efficiency with which countries employ human capital. Third, we highlight the importance of sector-level analyses by showing that productivity differences play a smaller role in construction, distribution services, and financial and business services than in manufacturing and personal services.

JEL classifications: O41, O47, E23

Keywords: Development accounting, Sector level, Production function, Elasticity of substitution, Total factor productivity

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1 Introduction

Differences in per worker output levels across countries are vast: a worker in the United States produces more than the 70-fold output of a worker in Burundi, even when accounting for differences in price levels.[1] Even China or India only reach a fifth and a seventh of the US per worker output level, respectively. Those output differences largely pin down global variations in poverty rates and other important welfare measures (Dollar et al., 2015, 2016), and are hence important to understand in more detail.

Development accounting is a key macroeconomic tool to study those output differences. Conventional development accounting plugs measures of production factors, such as capital and labor of different skill types, into a Cobb-Douglas production function and labels the residual output variation that is unexplained by this production structure as "(total factor) productivity" (TFP). This residual usually accounts for about half of cross-country output variation (e.g., Hsieh and Klenow, 2010) but it has been heavily debated whether it indeed captures efficiency differences across countries or is merely a "measure of our ignorance about the causes of economic growth" (Abramovitz, 1956). Moreover, this TFP residual is factor-neutral in the sense that it augments physical and human capital in a uniform way. This neglects the possiblity of factor-biased technological change and that countries may refrain from using available technologies because they are not appropriate for their production factor endowments (Basu and Weil, 1998; Acemoglu and Zilibotti, 2001). For example, a capital-poor farmer in rural India will be less likely to adopt a modern 5G or artificial intelligence technology than a capital-rich US agrobusiness, even if both have the same access to this technology.

Several studies have hence investigated how the results of development accounting depend on the functional form of the aggregate production function (Caselli, 2005; Pandey, 2008; Aiyar and Dalgaard, 2009). This line of research is supported by more recent evidence against the empirical plausibility of the Cobb-Douglas production function (e.g., León-Ledesma et al., 2015; Knoblach et al., 2019; Gechert et al., 2022). Another line of development accounting research increasingly focused on measuring input factors accurately, placing particular emphasis on the human capital measure.[2] Finally, a third line of development accounting research has begun to complement the country-level perspective with sector-level analyses (Hsieh and Klenow, 2007; Duarte and Restuccia, 2010; Herrendorf and Valentinyi, 2012; Duarte and Restuccia, 2019). However, due to the lack of sector-specific data on internationally com-

[1] PWT10.0 by Feenstra et al. (2015), rgdpo/emp, data for 2019.

[2] Among others, Hendricks (2002); Caselli (2005); Caselli and Coleman (2006); Hanushek and Woessmann (2012); Caselli and Ciccone (2013); Jones (2014); Hendricks and Schoellman (2018); Caselli and Ciccone (2019); Hendricks and Schoellman (2023). The development accounting literature is vast. Section 2 will review some of the key contributions.

parable prices and inputs, sector-level studies had to largely abstract from methodological advances regarding input measurement and functional form assumptions made in the development accounting literature.

The main contribution of our paper is to unite those lines of development accounting research. More precisely, we mainly rely on Caselli's (2005) "appropriate technology" framework, which allows for the possibility that firms have access to a whole menu of feasible technology combinations that are not factor-neutral. We apply this framework to a tradeable 'market' sector and five different subsectors and allow for a sector-specific constant elasticity of substitution (CES) production function. Because this CES function nests the Cobb-Douglas production function as a special case, we can benchmark our CES results to the conventional development accounting framework. We overcome previous lack of sector-specific data on internationally comparable prices and inputs by combining the Socio-Economic Accounts in the World-Input-Output Database (WIOD-SEA) with multilateral relative industry-level prices from Inklaar and Timmer (2014). While the availability of different labor skill types on the sector level limits us to the 2014 WIOD-SEA release and hence the period 1995-2007, this allows us to construct sectoral output[3] nominated in international purchasing power parities (PPP) for 38 countries. Our CES estimates are based on a supply-side system approach using non-linear seemingly unrelated regression (NLSUR) estimation (Klump et al., 2007; León-Ledesma et al., 2010).

Our results provide three key findings about the sources of cross-country output differences. First, productivity differences across countries are largely pinned down by the efficiency at which they employ human capital. This sector-level evidence is in line with Caselli's (2005) economy-wide finding that rich countries use human capital more efficiently but physical capital less efficiently compared to poor countries.[4] The underlying economic intuition for this finding can be summarized as follows: Our CES estimates clearly suggest that physical and human capital are gross complements in all sectors. It is hence reasonable for countries to opt for technologies that augment the relative scarce factor because the increase in the effective input of the scarce factor raises the marginal productivity of the abundant,

[3] In this paper, sectoral output refers to value added, not gross output. The terms output and value added will be used interchangeably.

[4] This paper uses the term "productivity" to refer an index that captures the ratio of output to inputs. The "efficiency" terms describe the components that transform the "raw" input measures (e.g., physical capital) into *effective* inputs. Finally, "*technical* efficiency" states whether a country operates at the technology frontier, or beneath it. Put differently, there is a discrepancy between the actual output and the maximum potential output. Note that a country can get more productive, even though input factors are used (technical) efficiently (e.g., by using a different input mix). Also, a country can be less efficient in using an input factor, although it is technical efficient. The latter differentiation will become important in the appropriate technology framework. The paper does *not* consider *"allocative* efficiency" of input factors across production units.

but relatively unproductive, input factor relatively to the scarce factor. Since lower-income countries have a higher human-to-physical-capital-ratio, differences in the efficiency at which they employ human capital must drive output per worker differences across countries.

A second result of our exercise is that, compared to the standard Cobb-Douglas set-up, the appropriate technology framework with physical and human capital as complements attributes a smaller fraction of the cross-country output per worker variation to barriers to technology adoption in all sectors.[5] Again, this is an intuitive result from our CES estimates: because physical and human capital are more complementary than in the Cobb-Douglas case, scarcity of one production factor cannot be as easily substituted by another production factor. Lack of a scarce production factor has accordingly larger consequences for output and leaves less residual variation in output unexplained.

Third, our results show considerable cross-sector heterogeneity regarding the proximate sources of output per worker variation. Barriers to technology adoption can explain a larger fraction of the output per worker variation in Manufacturing and Personal Services (around 30%) than in Construction, Distribution Services, and Financial and Business Services (almost nothing). This emphasizes the importance of complementing development accounting on the aggregate level with sector-level analyses based on different specifications to provide better orientation for economic theory and policy making.

Our paper adds to the vast literature on development accounting, and particularly complements sector-level studies by Hsieh and Klenow (2007) and Herrendorf and Valentinyi (2012). The former find that developing countries have particularly low productivity in producing investment goods and tradable goods relative to nontradables. The latter find that the productivity disparity in Manufactured Consumption is about equal to the aggregate disparity, lower in Services, and larger in Equipment, Construction, and Food. However, due to a lack of sectoral input data, both studies require the assumption that factors are perfectly mobile across sectors. This assumption stands in strong contradiction to the central theme of the growing misallocation literature (e.g., Hsieh and Klenow, 2009; Vollrath, 2009). Moreover, while Hsieh and Klenow (2007) omit human capital entirely, Herrendorf and Valentinyi (2012) build on strong functional form assumptions for both the human capital input and the production function. In contrast, this paper considers the recent debate on the importance of the substitution elasticity between different skill types and cross-country differences in the relative efficiency levels of skill types (Caselli and Ciccone, 2013; Jones, 2014; Caselli and Ciccone, 2019). Moreover, we also considers the "appropriate technology" specification in Caselli (2005) to allow for non-neutral technology of physical and human capital.

[5] Note that from the Cobb-Douglas perspective of factor-neutral technological change, technology differences across countries are caused by *barriers* to technology adoption: some countries employ their input factors at a lower efficiency level because they have no access to superior technology.

Our paper additionally adds to the vivid literature on the substitution elasticity between capital and labor (Duffy and Papageorgiou, 2000; Klump et al., 2007; León-Ledesma et al., 2010; Chirinko and Mallick, 2017; Knoblach et al., 2019; Gechert et al., 2022). This elasticity has important implications for the functional income distribution and a wide range of other macroeconomic outcomes (see Gechert et al., 2022, for an overview) but cross-country sector-level evidence was largely absent to date. In line with most recent economy-wide findings, our results strongly suggest an elasticity of substitution below unity in all sectors, more precisely in the range of 0.4 to 0.6. This suggests that we have to look beyond Piketty's (2014, ch.6) hypothesis that capital accumulation is the source of the declining labor share. Promising alternatives involve market power and technology shocks. Since those are likely to be sector-specific and the response of the labor share crucially depends on the substitution elasticity (Grossman and Oberfield, 2022; Bergholt et al., 2022), our approach and results will further inform this important macroeconomic line of research.

The remainder of this paper is structured as follows. The next section reviews selected work of the development accounting literature and links it to work that quantifies the implications of sectoral productivity differences across countries. Section 3 presents the model specification and section 4 introduces the data. Section 5 describes the estimation method for the elasticity of substitution and presents sector-level estimates. The development accounting results are presented in section 6. Section 7 concludes.

2 Development accounting on the aggregate and sector level

Development accounting links output y to inputs with a production function $F(\cdot)$.[6] The standard workhorse production function is a Cobb-Douglas (CD) function

$$y = Ak^{\alpha}h^{1-\alpha} \quad \alpha \in (0,1) \tag{1}$$

where y, k, and h are output, physical capital, and human capital, in per worker terms respectively. The parameter α defines the output elasticity of each factor and A represents a productivity term, often termed total factor productivity (TFP). With data on inputs and knowledge of α, we can obtain

$$y_{factor} = k^{\alpha}h^{1-\alpha} \quad \alpha \in (0,1) \tag{2}$$

[6]For a detailed overview of the development accounting literature, we refer the reader to the excellent summaries provided by Caselli (2005), Hsieh and Klenow (2010), and Jones (2016).

which is the output per worker that is due to factor inputs only. Using a variance decomposition, we can then gauge to what extent differences in input factor quantities account for output per worker differences. Following Caselli (2005), we call this fraction *success* and define it as

$$success = \frac{var\left[ln(y_{factor})\right]}{var\left[ln(y)\right]} \tag{3}$$

The residual fraction that is not explained by the contribution of input quantities is attributed to differences in productivity, A. This means that productivity captures the effects of a myriad of determinants of the efficiency of factor usage, such as scientific knowledge, market institutions, property rights, public infrastructure, and government policies. Much of the progress in the development literature over the past two decades can be understood as an effort to, as Caselli (2005) puts it, "chipping away" the productivity residual by improving the measures of output and inputs and considering different functional forms for $F(\cdot)$.

Development accounting in practice: prices and output elasticities

The production function in equation (1) helps to organize the progress in the development accounting literature. We want to start with the measurement of y, defined as output per worker. While measuring quantities is generally less problematic, the central issue in development accounting is to measure *(relative) prices* as precise as possible. On the output side, an appropriate comparison across countries requires not only a conversion into a common currency, but also to account for the fact that "the law of one price" does generally not hold. Instead, richer countries tend to have a higher relative price level, which is known as the Penn-effect (Samuelson, 1994; Inklaar and Timmer, 2014).

While it has been standard in cross-country studies to measure aggregate output in PPPs, sector-level studies have long been constrained by a lack of comparable relative prices across a large set of countries. For this reason, early productivity comparisons on the sector- or industry-level have mostly been restricted to a small number of advanced economies (e.g., Baily and Solow, 2001). More recently, Duarte and Restuccia (2010) use a model calibrated to the U.S. to back out sector-specific PPP-conversion factors for a sample of 29 countries. Herrendorf and Valentinyi (2012) use information on final expenditures, prices, and quantities of 30 good categories to construct output series for five sectors for a sample of 86 countries.[7] Parallel to these individual efforts, a consortium of research institutes and national statistical institutes has started an ongoing large-scale project that addresses the need for consistent

[7] To do so, they have to assume that purchased quantities equal domestically produced quantities, which results in a lower bound on the cross-country productivity disparity.

industry output data across countries (O'Mahony and Timmer, 2009; Timmer et al., 2015).[8] One key outcome of this project is a set of relative industry prices for 35 industries in 39 countries, which are constructed by combining harmonized country-specific Supply and Use tables with new and comprehensive data from the International Comparisons Program (ICP) (Inklaar and Timmer, 2013, 2014).

Prices are also vital in the measurement of the input factors and to quantify how inputs translate into outputs. Given equation (1), the output elasticities of the input factors are governed by the unobserved parameter α. To determine a value for α, development accounting commonly assumes that factors get paid their marginal products.[9] In this case, α can be derived from factor revenue shares. Unfortunately, labor income of self-employed is not registered in the National Accounts in many countries. For this reason, it is now common practice to impute self-employed income. Following the seminal paper by Gollin (2002), the standard assumption is that self-employed earn the same average wage per hour as employees. The evidence on these adjusted factor shares suggest that α differs across countries, but there seems to be no systematic correlation between y and α (Gollin, 2002; Bernanke and Gürkaynak, 2002; Bentolila and Saint-Paul, 2003; Feenstra et al., 2015). The latter finding suggests that setting a common value for α will unlikely bias the results in any particular direction, so that it is standard practice to impose the U.S capital share of 0.3-0.4 on all countries.[10] In fact, this fallback has also been applied in sector-level studies to overcome the scarce cross-country information on sectoral factor shares (e.g., Caselli and Coleman, 2001; Caselli, 2005; Hsieh and Klenow, 2007; Bosworth and Collins, 2008; Vollrath, 2009; Herrendorf and Valentinyi, 2012; Duarte and Restuccia, 2019). It is worth noting, however, that Caselli (2005) terms the value of α to be a "sensitive choice" in development accounting, as small increases in α lead to non-negligible increases in *success.*

Capital in development accounting

A severe limitation for sector-level studies is the lack of sectoral input data. While crude labor input measures (e.g., number of workers) are available, information on physical and/or human capital is usually based on theoretical concepts (Hsieh and Klenow, 2007; Restuccia and Rogerson, 2008; Duarte and Restuccia, 2010, 2019). Particularly, physical capital service is commonly defined as a weighted sum of past investments in different asset types, minus

[8] Two databases emerged from this project: 1) the KLEMS database and 2) WIOD.

[9] In general, the underlying working assumptions are competitive output and factor markets, full input utilization and constant returns to scale. Working with a Cobb-Douglas function in the form of equation (1) implies the latter. In order to derive α it is sufficient that the average earnings of the input factors are proportional to the value of their marginal products.

[10] See e.g., Hall and Jones (1999); Caselli (2005); Caselli and Coleman (2006); Pandey (2008); Aiyar and Dalgaard (2009); Hanushek and Woessmann (2012); Herrendorf and Valentinyi (2012); Jones (2014, 2016)

depreciation, where weights are given by relative efficiencies and measured by the the relevant user cost (or rental price) of capital. The argument that relative prices inform about relative efficiencies also plays a central role in the large literature that has been devoted to the role and measurement of human capital. In its simplest form, the human capital function can be written as

$$H = hL \tag{4}$$

where L is a raw labor input and h is an efficiency parameter that transforms L into a measure of human capital services. Given that data is provided for discrete groups of workers, equation (4) slightly modifies into

$$H = \sum h_k L_k \tag{5}$$

Either way, the problem is that the efficiency parameter, h, is unobserved. The standard approach in the development accounting literature to solve this issue is to approximate differences in the service flows of workers through information on educational attainment. More precisely, the human capital service coming from worker k in country c is defined as $h_{ck} = e^{\phi_{ck} s_{ck}}$, where ϕ represents a Mincerian coefficient - i.e., the percentage wage gain associated with an extra year spent in school - and s represents the duration in years of schooling.[11]

Imperfect substitution of skill types

By construction, equation (4) implicitly assumes that workers with different skills are perfect substitutes. While this assumption is standard in development accounting, there is now convincing evidence that the assumption of perfect substitutability among different schooling levels should be discarded (Ciccone and Peri, 2005; Autor et al., 2008; Mollick, 2011). Caselli and Coleman (2006) examine the implications for development accounting in a model with two types of workers: low- and high-skilled. Note that this means that they target the functional form, $F(\cdot)$, that specifies how production units generate output from inputs. Specifically they replace equation (1) by

$$y = k^{\alpha} \left[(A_{LL} h_{LL})^{\gamma} + (A_{LH} h_{LH})^{\gamma} \right]^{\frac{(1-\alpha)}{\gamma}} \tag{6}$$

where h_{LL} is unskilled labor and h_{LH} is skilled labor. The parameters A_{LL} and A_{LH} are

[11] A major limitation for sector-level development accounting is that comparable sector information on s and ϕ for multiple countries do not exist. See the assumptions in Herrendorf and Valentinyi (2012) for obtaining sectoral estimates of H as defined in (4).

efficiency terms that augment unskilled and skilled labor, respectively. The parameter γ governs the elasticity of substitution, $\eta = 1/(1-\gamma)$, between the two skill types. Heuristically, the implications of imperfect substitution can be best understood by distinguishing between a quantitative and qualitative effect. With perfect substitution, higher skill levels get weighted more (quantitative). With imperfect substitution, workers of different skills are fundamentally different and cannot replace each other fully (qualitative).

The key feature in Caselli and Coleman (2006) is that productivity differences across countries are not due to *uniform* efficiency differences, but rather due to *skill-specific* efficiency differences, captured by A_{LL} and A_{LH}. In this framework, Caselli and Coleman (2006) show that countries adopt technologies that are appropriate given their endowment of low- and high-skilled workers.[12] More precisely, assuming that low- and high-skilled workers are imperfect substitutes in production, countries adopt technologies that rise the *relative* efficiency of the abundant worker type. Caselli and Ciccone (2013) pick up this finding to show that the case of perfect substitution maximizes human capital difference across countries.[13]

Non-neutral technical change

The notion that efficiency differences are unlikely *uniform* for different skill types naturally extends to considering *factor-specific* efficiency differences. Put differently, by working with the Cobb-Douglas production function stated in equation (1), standard development accounting assumes that productivity augments physical and human capital in a *factor-neutral* way. Some countries simply use all of their inputs more efficiently than others. However, Caselli (2005) presents convincing evidence that rich countries use human capital more efficiently but physical capital less efficiently compared to poor countries, relatively and absolutely.[14]

To consider factor-specific efficiency differences, it is necessary to rewrite the production function not in a multiplicative, but in an additive form. That is, we have to replace the Cobb-Douglas function with a CES production function in the form

$$y = \left[\alpha \left(A_K k\right)^{\rho} + (1-\alpha)\left(A_H h\right)^{\rho}\right]^{\frac{1}{\rho}} \tag{7}$$

where A_K and A_H are efficiency terms that augment physical and human capital, respectively. The parameter ρ governs the elasticity of substitution, $\sigma = 1/(1-\rho)$, between the two

[12] Acemoglu and Zilibotti (2001) also employ the appropriate technology hypothesis to argue that even when all countries have access to the same set of technologies, there will still be large aggregate productivity differences across countries.

[13] For another perspective see Jones (2014) and the rejoinder by Caselli and Ciccone (2019).

[14] This finding is robust to different elasticities of substitution between physical capital and human capital and for plausible cross-country variation in the capital revenue share (Caselli, 2005).

inputs. Note that it is straightforward to further account for imperfect substitution of skill types by defining h as in equation (6). Using equation (7), Caselli (2005) proposes two set-ups. In the first, he imposes the U.S. efficiency terms, $A_{K,US}$ and $A_{H,US}$, on all countries. In the second, he assumes that countries choose *appropriate* efficiency terms from a set of available technologies. In both set-ups, his key finding is that the fraction of output per worker differences explained by barriers to technology adoption is highly positively sensitive to values of σ. This finding is supported by Aiyar and Dalgaard (2009). The key question then is: what is the value of σ?

By now, there is a large set of estimates for σ on the aggregate level. Although still a heavily debated topic, the majority of estimates suggest that σ is below unity; that is, physical and human capital are gross complements in production.[15] In contrast, estimates at lower levels of aggregation are quite scarce. Aside from measurement issues regarding the input factors, a key limitation for sector-level development accounting is thus the lack of appropriate sector values of σ. Motivated by this, a key contribution of this paper is to estimate sector-specific production functions and obtain appropriate values of σ that can be used in a sector-level accounting exercise.

3 Development accounting with CES functions

This sections specifies the model that we will bring to the data in order to find an approximate answer to the question: what fraction of the (logarithmized) output per worker variation remains, assuming that all countries have access to the same technology? Recall from the previous section that we capture this fraction by the measure *success.* In order to generalize the accounting approach to more flexible functional forms, we replace the factor-only model, y_{factor}, with y_{hyp}. The latter states a country's hypothetical output per worker that could be achieved if all barriers to technology adoption would be eliminated, ceteris paribus. Using y_{hyp}, we compute

$$success_{it} = \frac{var\left[ln(y_{hyp})\right]}{var\left[ln(y)\right]} \tag{8}$$

where the indices i and t clarify that we perform the development exercise for each sector and time period individually. A problem with the *success* measure as defined in equation (8) is that it is sensitive to outliers. We therefore follow the convention and obtain an alternative

[15] See, e.g., Antras (2004); Chirinko et al. (2004); Klump et al. (2007); Oberfield and Raval (2014); Knoblach et al. (2019); Chirinko and Mallick (2017). Conversely, Duffy and Papageorgiou (2000) and Karabarbounis and Neiman (2014) advocate a value of above one. We will return to this point in section 5.

measure based on an inter-percentile differential. More specifically, we obtain

$$success_{it}^{90/10} = \frac{y_{hyp}^{90}/y_{hyp}^{10}}{y^{90}/y^{10}} \tag{9}$$

which compares what the 90th-to-10th percentile ratio would be in the counterfactual world, to the actual value. Clearly, which inter-percentile differential we consider is a somewhat arbitrary choice. This being said, the purpose of $success^{90/10}$ is not only to validate the absolute values of *success*, but differences across sectors and specifications in particular.

To obtain y_{hyp}, we need to specify $F(\cdot)$. We start by defining output per worker in each country-sector as

$$y_{ci} = \frac{Y_{ci}}{L_{ci}}$$

In each country-sector, a representative firm generates output using a CES production function

$$Y_{ci} = \left[\alpha_{ci}\left(A_{ci}^{K} K_{ci}\right)^{\rho_i} + (1-\alpha_{ci})\left(A_{ci}^{H} H_{ci}\right)^{\rho_i}\right]^{\frac{1}{\rho_i}} \tag{10}$$

where the parameter ρ governs the elasticity of substitution, $\sigma = 1/(1-\rho)$.[16]

We define H_{ci} as a CES aggregate of three types of workers

$$H_{ci} = Q_{ci}\left[\left(h_{ci}^{LL} LL_{ci}\right)^{\gamma_i} + \left(h_{ci}^{LM} LM_{ci}\right)^{\gamma_i} + \left(h_{ci}^{LH} LH_{ci}\right)^{\gamma_i}\right]^{\frac{1}{\gamma_i}}, \tag{11}$$

where LL, LM, and LH capture the hours worked by low-, medium-, and high-skilled workers, respectively. The parameters h^{LL}, h^{LM} and h^{LH} are (efficiency) coefficients that convert hours worked into productive services, Q captures schooling quality, and the elasticity of substitution between the skill types is defined as $\eta = 1/(1-\gamma) > 0$. This follows the approach in Caselli and Coleman (2006), Jones (2014), and Caselli and Ciccone (2019). Note that for $\gamma \to 1$ and $\rho \to 0$, equation (10) collapses to a standard Cobb-Douglas production function. In this case, A^K and A^H are no longer independently identifiable. A more thorough economic interpretation of equation (11) is provided in Appendix B.1.

Combining equations (7) and (11) defines the production function $F(\cdot)$. The remaining question is what values to plug into $F(\cdot)$. For now, we want to focus on the parameters A_{ci}^{K} and A_{ci}^{H}. Recall that we want to find the variation in output per worker assuming that all countries have access to the same technology. As noted earlier, the additive nature of equation (7) requires to impose specific values for A_{ci}^{K} and A_{ci}^{H}. Importantly, the results

[16] See appendix D for an in-depth discussion of alternative ways to consider non-neutral technology such as Harrod-neutrality like in Aiyar and Dalgaard (2009) and Mello and de Souza Rodrigues (2017).

are sensitive to these values. We follow Caselli (2005) and consider a thought-experiment where countries choose technologies that are most appropriate for their factor endowments. Specifically, we use the first-order condition of a representative firm to calculate

$$\alpha_i \left(A_{ci}^K\right)^{\rho_i} = LS_{ci} * \left(\frac{Y_{ci}}{K_{ci}}\right)^{\rho_i} \tag{12}$$

$$(1-\alpha_i) \left(A_{ci}^H\right)^{\rho_i} = LS_{ci} * \left(\frac{Y_{ci}}{H_{ci}}\right)^{\rho_i} \tag{13}$$

where LS_{ci} represents the country-sector-specific labor share in value added. Given values for α and ρ, equation (12) and equation (13) thus allow us to obtain a set of technology combinations (A_{ci}^K, A_{ci}^H). Heuristically, these combinations can be thought of as the existing stock of technology blueprints in the world. To each country and sector, we then allocate the combination of (A_{ci}^K, A_{ci}^H) that maximizes output per worker, ceteris paribus. Importantly, this means that countries adopt the technology combination that is most appropriate given their factor endowments. Hence, in the counterfactual world, all countries will be *technical* efficient (i.e., operate at the technology frontier), but can differ in the efficiency levels (A^K, A^H) with which they employ physical and human capital. We end up with y_{hyp} for each country and sector, which we can then plug into equation (8). In this set-up, *success* can thus be interpreted as stating the fraction in output per worker variation *not* explained by barriers of technology adoption, while allowing for technology differences, with technology comprising a myriad of factors.

In principle, access to the global set of technology combinations should allow poor countries to at least partially remedy their unfavorable input factor mix. On the other hand, there is empirical evidence that the frontier technologies are more geared towards the relative factor endowments of rich countries (Timmer and Los, 2005; Jerzmanowski, 2007). To what extent access to the same feasible menu of technologies affects the cross-country variation in output per worker therefore depends on the distribution of existing factor endowments, country-factor-specific technology levels, and available frontier technologies in the sample. This should be kept in mind when interpreting the *success* ratio based on a CES specification.

4 Data and calibration

The output and input data used in this study come from the 2014 release of the Socio-Economic Accounts in the World-Input-Output Database (WIOD-SEA). The WIOD-SEA database has been constructed on the basis of national accounts data and harmonization procedures were applied in order to ensure international comparability. For the period 1995-2007, the 2014 version contains annual data for 35 industries in 40 countries (27 EU countries and 13 other major countries) on gross output and intermediate input at current basic prices, capital stock, as well as hours worked and labor compensation by skill type (low-, medium- and high-skilled) (Timmer et al., 2015).

A central issue for cross-country comparison of productivity levels is that value added is nominated in international purchasing power parities (PPP). Aside from containing information by skill type, the 2014 version of WIOD-SEA has the advantage that industries are classified according to the ISIC Rev. 3.1 classification. This allows to directly map the value added data to the multilateral relative industry-level prices recently published by Inklaar and Timmer (2014).[17] Relative industry-level prices allow to account for the fact that "the law of one price" does generally not hold. Instead, richer countries tend to have higher relative price levels, which is known as the "Penn effect" (Samuelson, 1994; Inklaar and Timmer, 2014). Moreover, there is substantial variation in relative prices across industries (see table 14 in appendix A). Adjusting output data by relative prices on the industry-level thus represents a major feature of this study.

There are a few comments that need to be made. First, cross-country comparisons of productivity measures in non-market services are highly problematic due to the lack of market prices. To ensure a decent data quality, we restrict the cross-country comparison to the five market sectors listed in table 1.[18] On average, the five sectors account for an cumulative share of 2/3 in each country's total value added and hours worked. Second, relative price data is only available for the year 2005. We therefore proceed as follows. We deflate gross outputs and intermediate inputs using the industry-level price deflators integrated in WIOD-SEA and obtain growth rates of both series. An advantage of the double-deflated value-added method, oppose to a single-deflated value-added measure, is that it can account for changes in the relative prices of intermediate inputs to outputs. The real growth rates are then used to extrapolate the output and intermediate input series, which are converted into PPPs for

[17] We convert value added into PPPs on the industry-level (35 industries). We have three industry-country observations for which we have data on outputs and inputs in national currency but no information on relative prices. We use information on relative prices from those countries that have the highest price correlations with the country that has a missing observation. Specifically, we impose the relative industry price level adjusted by the ratio of the mean price levels of the two countries.

[18] This (dis)aggregation is consistent with Jorgenson and Timmer (2011).

the available year 2005.[19] In a last step, we construct a value added series in constant 2005 PPPs by subtracting intermediate inputs from gross output, both nominated in constant PPPs. Unfortunately, no information on relative prices are available for Taiwan.

Table 1: Sector overview

Abbr	**Sector Name**	**ISIC Rev 3.1 code**
Const	Construction	E
Distrib	Distribution Services	50–52 and 60–64
FinBus	Finance and Business Services	J and 71–74
Manu	Manufacturing	15–37
Pers	Personal Services	H, O, and P
Market	Market sector	Sum of the above

Note: Description of ISIC Rev 3.1 codes. *50:* Sale, Maintenance and Repair of Motor Vehicles and Motorcycles; Retail Sale of Fuel. *51:* Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles *52:* Retail Trade, Except of Motor Vehicles and Motorcycles; Repair of Household Goods *60:* Inland Transport *61:* Water Transport *62:* Air Transport *63:* Other Supporting and Auxiliary Transport Activities; Activities of Travel Agencies *64:* Post and Telecommunications *J:* Financial Intermediation *71-74:* Renting of M& Eq and Other Business Activities *H:* Hotels and Restaurants *O:* Other Community, Social and Personal Services *P:* Private Households with Employed Persons

Regarding the factor inputs, WIOD-SEA provides data on real physical capital stocks nominated in constant 1995 local currencies. To obtain comparable real physical capital stocks across countries, we use the exchange rate from PWT 8.1 (Feenstra et al., 2015) to convert the series into US$ in the year 1995. Using growth rates from the real capital stock data nominated in national currencies, we extrapolate the series to 2007.

Another contribution of this paper is to construct sectoral human capital inputs in the form

$$H_{cit} = Q_c h_{ci}^{LL} LL_{cit} \left[1 + \left(\frac{h_{ci}^{LM}}{h_{ci}^{LL}} \right)^{\gamma_i} \left(\frac{LM_{cit}}{LL_{cit}} \right)^{\gamma_i} + \left(\frac{h_{ci}^{LH}}{h_{ci}^{LL}} \right)^{\gamma_i} \left(\frac{LH_{cit}}{LL_{cit}} \right)^{\gamma_i} \right]^{\frac{1}{\gamma_i}} \tag{14}$$

(cf. equation (18) in Appendix B.1). To obtain equation (14), we require information on the raw labor input per skill type (LL, LM, LH), relative efficiency parameters ($\frac{h^{LM}}{h^{LL}}$ and $\frac{h^{LH}}{h^{LL}}$), the quality of schooling (Q), and the parameter defining the elasticity of substitution across different skill types (γ). A unique feature of WIOD-SEA is that it reports hours worked and shares of overall labor compensation for three skill types of workers. These skill types are classified on the basis of educational attainment levels as defined in the 1997 International

[19]While this approach is not uncommon, it should be pointed out that the underlying assumption is that cross-country industry-level prices deflators are constant over time. Given the time horizon 1995-2007, this assumption seems defensible.

Standard Classification of Education (ISCED) shown in Appendix A, table 5.Given that factors get paid their marginal products, this allows to directly obtain skill-specific average wages by dividing the payments to each skill type by the respective hours worked.[20]

While WIOD-SEA in principle provides all the information needed to obtain equation (14), the broad classifications into three skill groups has weaknesses regarding the comparability of educational attainment and qualifications across countries. We thus augment the skill inputs indirectly using country information on the schooling attainment and duration. See Appendix B.2 for details.

Tables 6 and 7 in Appendix A report some basic descriptives from the dataset. For the aggregate Market sector, output per worker in the richest country (Luxembourg) is 11 times higher than in the two poorest countries in the sample (Indonesia and India). On average, output per worker is highest in Finance and Business Services. It is worth noticing that based on the summary statistics, cross-sector variation in relative efficiency levels appear to be small. This indicates that the assumption of common returns to schooling for low-skilled across sectors within a country as imposed by equation (22) has only limited quantitative implications. In line with previous evidence, human capital differences across countries are rather moderate if skill types are perfect substitutes. Skill supplies in each sector vary widely across countries, which supports the decision to differentiate between three types of workers oppose to just two.

For the elasticity of substitution across those skill types, we consider plausible estimates of $\eta \in [1.6, 2, 4, \infty]$, as motivated by previous literature. For the case of skill types being perfect substitutes, tables 7 and 13 show that human capital per hour worked is moderately (0.4) and per worker (0.2) weakly correlated with output per worker. As expected, the correlation is higher (0.7 and 0.4) when skill types are weighted by common relative efficiency levels. Appendix tables 10, 11, and 12 present additional information on the relative efficiency levels and human capital per worker input for different elasticities of substitution across skill types. Note that for lower elasticities of substitution, the relative efficiency levels in skill abundant countries increase compared to those in low-skill abundant countries. As in Jones (2014), a consequence of this is that cross-country differences in human capital per worker increase dramatically (appendix table 12). This has, however, no effect on the correlation between human capital per worker and output per worker (appendix table 13). Since differences and ranking in human capital per worker across countries for low skill substitutability $\eta \leq 2$ appear economically implausible (see appendix table 12), we complement the traditional development accounting set-up of perfect skill substitutes with the scenario of imperfect

[20] More precisely, we estimate growth rates of real wages in constant national currency. For the year 2005, we convert wages into U.S. Dollar using the PWT8.1 exchange rate. We then use these growth rates to extrapolate the wages to 1995 and 2007.

substitution based on the assumption that $\eta = 4$.

5 Estimation of σ

The final parameters to be determined are the elasticities of substitution across physical capital and human capital, σ_i (defined by ρ_i), and across skill types, η_i (defined by γ_i). This paper estimates the parameters based on a normalized supply-side system of equations.[21] Normalization essentially implies writing the production function in an index form as

$$\frac{Y_{cit}}{Y_0} = [\alpha_{ci} \left(A_{cit}^K \frac{K_{cit}}{K_0} \right)^{\rho_i} + (1 - \alpha_{ci}) \left(A_{cit}^H \frac{H_{cit}}{H_0} \right)^{\rho_i}]^{\frac{1}{\rho_i}} \tag{15}$$

where Y_0, K_0, and H_0 represent the points of normalization. Importantly, normalization allows to isolate the effect of σ from changes in the distribution parameter, α. As pointed out by Klump and co-authors in a series of publications, the distribution parameter in a CES production function is not "deep" (Klump and de La Grandville, 2000; Klump et al., 2007; Klump and Saam, 2008; Klump et al., 2012). Instead, it is a function of the elasticity of substitution itself. This feature complicates the task to choose appropriate initial values for the parameters to be estimated. Conversely, normalization allows to fix the distribution parameter so that they are no longer a function of the elasticity of substitution. More precisely, α can be interpreted as the revenue share of physical capital at the point of normalization.[22]

Following the intuition that observations that are represented by the same production function should have the same normalization point, we normalize each sector production function with the geometric average over countries and time. That is, we define $Y_0 = \overline{Y}$, $K_0 = \overline{K}$, $H_0 = \overline{H}$, $LL_0 = \overline{LL}$, $LM_0 = \overline{LM}$, and $LH_0 = \overline{LH}$. Consequently, the distribution parameter α is set equal to the geometric average capital share.[23] To account for unobserved heterogeneity across countries, we introduce a parameter vector A_c. We further assume that factor-directed technical change, A^K and A^H, takes a linear form and is captured by ν_K and ν_H. Taking logarithms and adding an error term μ, results in the the following supply-side system (dropping the sector index for clarity)

[21] Klump et al. (2007) first implement the idea of normalization for the estimation of a supply-side system. More recent applications include Herrendorf et al. (2015) and McAdam and Willman (2018).

[22] It is worth noting that every CES function is at least implicitly normalized at point $Y_0 = K_0 = H_0 = 1$. Further note that this implies the counterfactual outcome that the real interest rate at the normalization point is equal to the capital income share.

[23] This implies a capital share of 0.41 in the Market sector, 0.34 in Construction, 0.43 in Distribution Services, 0.45 in Finance and Business Services, 0.44 in Manufacturing, and 0.32 in Personal Services. As a robustness test, we run several different specifications, including variants in which we estimate α from the data instead of fixing it to a specific value.

$$log\left(\frac{Y_{ct}}{\bar{Y}}\right) = log\left(A_c\right) + \frac{1}{\rho}log\left[\alpha\left(\frac{e^{\nu_K(t-t_o)}K_{ct}}{\bar{K}}\right)^{\rho} + (1-\alpha)\left(\frac{e^{\nu_H(t-t_o)}H_{ct}}{\bar{H}}\right)^{\rho}\right] + \mu_{ct} \quad (16)$$

$$log(w_{ct}) = log\left((1-\alpha)\frac{\bar{Y}}{\bar{H}}\right) + (1-\rho)log\left(\frac{Y_{ct}/\bar{Y}}{H_{ct}/\bar{H}}\right) + \rho\left(log\left(A_c\right) + \nu_H\left(t-t_o\right)\right) + \mu_{ct} \quad (17)$$

Since equation (16) is non-linear in ρ, we estimate equation (16) alone via non-linear regression and jointly with equation (17) as a supply-side system using feasible non-linear seemingly unrelated regression (FGNLSUR) for each sector individually. We consider different specifications including: pooled versus country-fixed effects; neutral ($\nu_K = \nu_H$) versus factor-directed technological change; and distribution parameter α calibrated and fixed or estimated. Standard error are bootstrapped.

Our preferred specification is the normalized supply-side system approach with a calibrated α and directed technological change (León-Ledesma et al., 2010). Despite its advantages, the short time dimension of the panel limits us to only allow for heterogeneity of σ across sectors but not across countries and time. To consider the impact of η on σ, we follow a grid search approach as proposed by Henningsen and Henningsen (2012). More precisely, we impose $\eta \in [2, 4, \infty]$.

For our preferred specification, table 2 presents sector-specific estimates of σ_i and corresponding 90%-confidence intervals based on bootstrap standard errors for different values of η_i. Note that σ_i is estimated to be below unity in all sectors and quite robust to different imposed values of η_i in most sectors.[24] Our estimates are well-aligned with sector-level estimates by Young (2013); Oberfield and Raval (2014) and Chirinko and Mallick (2017) and qualitatively in line with the below-unity aggregate substitution elasticity that Knoblach et al. (2019) and Gechert et al. (2022) find in their meta regression analysis. To better isolate the effects of σ_i and η_i, we will hold one of the parameters constant in the accounting exercise (and focus on the case of $\eta = 4$ compared to the baseline of perfect skill substitutability, as noted in the previous section).

Table 8 in Appendix A presents the estimation results for different specifications for the aggregate Market sector. The elasticity of substitution estimate is quite similar across the different specifications. Moreover, the technology parameters are of reasonable magnitude

[24]Not surprisingly, using the human capital measure constructed based on homogeneous skill efficiency levels leads to almost identical results in the case of skill types being perfect substitutes. Also, with H_{alt}, σ is even more robust to η.

Table 2: Sector estimates of σ for different η

		Market	Constr	Distrib	FinBus	Manu	Pers
		Human capital input with country-specific efficiency terms					
(1)	$\eta \to \infty$	0.49	0.45	0.53	0.57	0.52	0.46
		(0.45-0.54)	*(0.37-0.58)*	*(0.48-0.60)*	*(0.48-0.69)*	*(0.46-0.58)*	*(0.41-0.53)*
(2)	$\eta = 4$	0.49	0.44	0.53	0.63	0.52	0.45
		(0.45-0.55)	*(0.39-0.51)*	*(0.48-0.59)*	*(0.53-0.79)*	*(0.46-0.61)*	*(0.42-0.50)*
(3)	$\eta = 2$	0.61	0.51	0.64	0.82	0.66	0.52
		(0.53-0.71)	*(0.43-0.61)*	*(0.58-0.72)*	*(0.68-1.03)*	*(0.55-0.81)*	*(0.46-0.59)*
		Human capital input with homogeneous efficiency terms					
(4)	$\eta \to \infty$	0.50	0.47	0.54	0.54	0.53	0.48
		(0.46-0.55)	*(0.38-0.60)*	*(0.48-0.61)*	*(0.47-0.65)*	*(0.48-0.59)*	*(0.42-0.56)*
(5)	$\eta = 4$	0.50	0.47	0.54	0.54	0.52	0.48
		(0.46-0.56)	*(0.38-0.61)*	*(0.48-0.62)*	*(0.47-0.65)*	*(0.48-0.59)*	*(0.42-0.56)*
(6)	$\eta = 2$	0.50	0.47	0.54	0.54	0.52	0.48
		(0.46-0.56)	*(0.39-0.61)*	*(0.48-0.62)*	*(0.47-0.65)*	*(0.47-0.58)*	*(0.42-0.57)*

Note: N = 494. Estimates of sector elasticities of substitution between physical capital and human capital, σ, based on different imposed values of η. 90% CI in parentheses. Standard errors are bootstrapped based on 500 iterations. Estimation applies a two-step FGNLSUR on a normalized supply side system. α is set to 0.41 in Market; 0.45 in Const; 0.53 in Distrib; 0.57 in FinBus; 0.52 in Manu; and 0.46 in Pers.

suggesting a growth rate of 1-2% p.a. in most specifications. Sector results for alternative specification are shown in appendix C. Here, the increase in efficiency due to the increase in the degrees of freedom is even more pronounced. Overall, the same conclusions hold and strongly suggest sector-level substitution elasticities that are inconsistent with Cobb-Douglas and in favor of a more flexible CES specification.

6 Development accounting results

6.1 Aggregate Market sector

We start the discussion of results with a baseline Cobb –Douglas specification for the aggregate Market sector as a reference, where we assume a common capital share of 0.41 across countries.[25]

Results are reported in panel A, column (1) of Table 3, which states the *success* ratio (i.e., the fraction of cross-country output per worker variation that cannot be explained by differences in barriers to technology adoption). Row (3) constitutes the most-standard reference case (with common capital share and human-capital-augmented labor) and the value of 0.52 suggests that differences in factor endowments account for slightly more than half of the cross-country variation in log output per worker, which is largely consistent with the standard macroeconomic literature.[26] Alternative specifications in panel A suggest an even smaller role for factor endowments, except for our alternative measure for human capital with common relative efficiency levels (see appendix B.2), which barely makes a difference. Notably, if we ignore human capital differences across countries (column (2)), the fraction of output variation explained by factor endowments decreases by about 15 percentage points to 37%. This suggests a relatively small role for human capital, which is at the lower end of previous findings (Caselli, 2005; Hsieh and Klenow, 2010).

This picture considerably changes if we allow for imperfect substitution of skill types in human capital, as depicted in panel B of Table 3 for the case of a skill substitution elasticity $\eta = 4$. Compared to the baseline in row (3), the success ratio increases by 19 percentage points to 71% in row (6). The increase is even larger when allowing for country-specific capital shares (rows (5) and (7)). It is important to note that this higher importance of human capital operates through the relative efficiency channel, i.e. due to the fact that that countries adopt technologies that are appropriate given their endowment of low and high-skilled workers (Caselli and Coleman, 2006). This becomes apparent by comparison with our alternative human capital measure in row (8), which imposes common relative efficiency levels across countries (see appendix B.2), and leaves the fraction of output variation explained by factor endowments virtually unchanged, compared to rows (3) and (4). From a policy perspective, this suggests that policies that foster skill creation (e.g., through education) by themselves might have limited effects on output per worker.[27] Table 9 in Appendix A shows that these

[25]All reported results are for 2007, the most recent year for which WIOD-SEA data are available. Results comparing developments over time are available upon request.

[26]Note that several other studies, which often assign a slightly higher importance to factor endowments, do not exclusively focus on the Market sector.

[27]Note that the assumption for H_{alt} in row (8) that two countries obtain the same relative efficiency levels

findings are robust to using the alternative measure based on the 90th-to-10th percentile ratio.

Table 3: *success* ratios for different specifications (2007)

		(1) Market	(2) Const	(3) Distrib	(4) FinBus	(5) Manu	(6) Pers
Panel A: Cobb-Douglas with perfect substitution							
(1)	with common α and L	0.43	0.48	0.54	0.87	0.29	0.32
(2)	with α and raw hours worked	0.37	0.49	0.47	0.70	0.28	0.26
(3)	with α and H	0.52	0.73	0.60	0.89	0.37	0.41
(4)	with α and H_{alt}	0.54	0.72	0.61	0.84	0.38	0.39
(5)	with H and country-specific α_c	0.43	0.91	0.49	0.72	0.35	0.41
Panel B: Cobb-Douglas with imperfect substitution of skill types							
(6)	with α and $\eta = 4$	0.71	1.12	0.80	1.17	0.47	0.62
(7)	with α_c and $\eta = 4$	0.68	1.36	0.75	1.27	0.47	0.70
(8)	with H_{alt}, α, and $\eta = 4$	0.55	0.73	0.62	0.85	0.39	0.41
Panel C: CES with (im)perfect substitution of skill types							
(9)	with H	0.97	0.83	0.93	2.10	0.65	0.51
(10)	with H and $\eta = 4$	1.05	1.34	1.17	2.23	0.71	0.80
(11)	with H_{alt}	0.94	0.72	0.92	2.26	0.61	0.49
(12)	with H_{alt} and $\eta = 4$	0.94	0.72	0.91	2.25	0.63	0.55
(13)	with H and adjusted frontier	0.80	0.93	0.89	1.59	0.58	0.56

Note: α is set to 0.41 in Market; 0.34 in Const; 0.43 in Distrib; 0.45 in FinBus; 0.44 in Manu; and 0.32 in Pers. H_{alt} uses common relative efficiency levels. σ is set to 0.49 in Market; 0.45 in Const; 0.53 in Distrib; 0.57 in FinBus; 0.52 in Manu; and 0.46 in Pers. In (13) the three most appropriate technology combinations are with withhold for each country.

Panel C of Table 3 presents the results for the appropriate technology framework with a CES production function, where we use the elasticity of substitution from row (1) in table 2, $\sigma = 0.49$. The results confirm Caselli's (2005) finding that a lower substitution elasticity σ increases the fraction of output variation that is explained by differences in factor endowments. In fact, rows (9)-(12) suggest that barriers to technology adoption can explain hardly any differences in cross-country output per worker.

The low importance of conventional 'productivity' differences in this setup is due to higher factor efficiency. Countries "choose" technologies that are most appropriate for their endowment structure. As physical and human capital are gross complements in production ($\sigma < 1$), countries will choose a technology combination that augments the relatively scarce factor in particular. This skews the ratio of marginal products in favor of the relatively

will only hold if one assumes that relative efficiency levels are solely driven by relative skill shares and ignores the role of institutions (Caselli and Ciccone, 2019).

abundant factor, thus improving overall factor efficiency. In fact, the data suggest that this is what countries actually do: the sample correlation between the human-to-physical capital ratio (i.e., h/k) and A_H/A_K is -0.55.

To what extend countries benefit from access to the technology frontier depends on whether the available menu of technology combinations is appropriate for a country's factor input mix. To illustrate this point, consider the cases of Belgium, the Netherlands, Ireland, and India in 2007, visualized in figure 1. As the country with the lowest h/k-ratio in the sample, Belgium (and each other green-dotted country) achieves the highest output per worker level the technology combination of Luxembourg, which offers the largest augmentation of human capital,A_H. For the Netherlands (and the other red-dotted countries), the largest output gains are associated with adopting the technology of Ireland, which has a very similar factor composition, but superior technology levels. In contrast, for Ireland, there exists no superior technology combination. Finally, as India is relatively abundant in human capital, output is maximized by using the technology of China, which heavily augments physical capital, A_K. This is plausible, as China is itself very human capital abundant.[28]

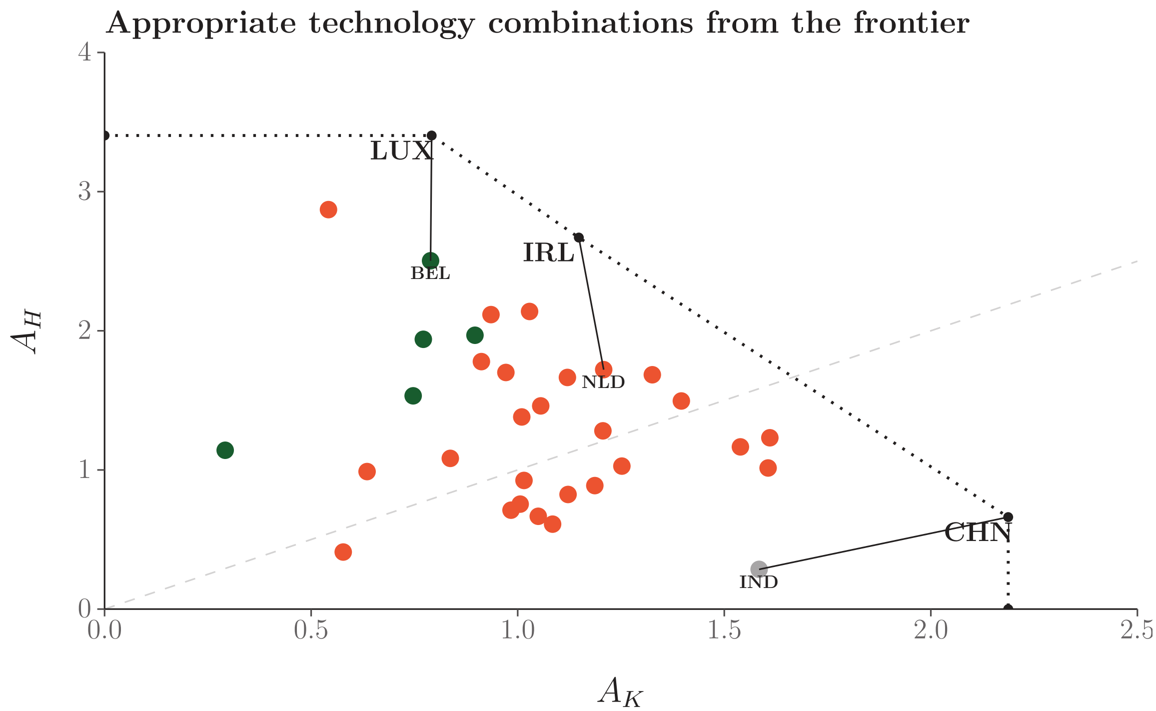
Our results depicted in Figure 1 imply that most countries are assigned a technology combination that increases the effective human capital input, both absolutely and relatively to physical capital.[29] In fact, several countries benefit from adopting Ireland's frontier technology through an increase in A_H at the cost of a lower A_K. This indicates that in most countries, physical capital is used relatively unproductively. Also, it means that the technology frontier contains technology combinations that particularly benefit countries that are relatively abundant in physical capital per worker. The larger *success* value in the CES specification can thus be explained by the fact that removing barriers to technology adoptions not only benefits poor countries, but also rich countries, which tend to be abundant in physical capital per worker. As a consequence, the variation in hypothetical output per worker, $ln(y_{hyp})$, is similar to the actual output per worker variation, which results in a *success* value close to one. This insight will be helpful to explain the sector-level results. For now, we conclude that *barriers* to technology adoption can explain only a small fraction of the output per worker variation in the sample.

As noted earlier, compared to the standard Cobb-Douglas set-up, the development accounting results based on CES functions are even more sensitive to the sample composition because it determines the available set of technology combinations. To check the robustness of the results, we consider three alternative measures. First, the $success^{90/10}$ value for the Market sector is 0.83 (Table 9). Second, to test whether the results are sensitive to the tech-

[28] It is worth noting that several countries are assigned a *lower* A_H or A_K for the benefit of a technology combination that increases the effective input of their scarce factor.

[29] Turkey, India, and China are the exceptions.

Figure 1:



Note: Own calculation based on equation 12 and equation 13. Countries displayed in green, orange, and grey maximize output per worker with the technology combination of Luxembourg, Ireland, and China, respectively. The dashed grey line represents the bisectrix.

nology frontier, we withhold the three most appropriate technology combinations for each country. Row (14) in table 3 shows that *success* decreases to 0.8; a rather moderate decline. Finally, the corresponding value of $success^{90/10}$ for this scenario is 0.7. It is worth noting that these values are not too far from Caselli's (2005) values of around 0.6 and 0.48 for *success* and $success^{90/10}$, respectively. The discrepancy can be due to the sample composition or differences between the Market sector and the aggregate economy, which Caselli uses in his analysis. All things considered, the findings based on the appropriate technology model suggests that barriers to technology adoption potentially play a smaller role than considered by the current consensus view derived from Cobb-Douglas specifications.

6.2 Sector-level results

Columns (2)-(6) in table 3 present the development accounting results for individual sectors and reveal substantial cross-sector heterogeneity regarding the proximate causes of output per worker differences.

Focusing on the Cobb-Douglas results in panel A first, productivity differences play the largest role in Manufacturing and Personal Services accounting for more than half of the output per worker variation across countries. Differences in factor endowments also leave more than 40% of the existing output per worker differences in Distribution Services. Conversely, they can explain more than 70% in Finance and Business Services. This is also the case in Construction once cross-country differences in human capital are taken into account, which increases *success* by 24 percentage points. Similar to the Market sector, human capital can explain between 10-20% of the output per worker variation in the remaining sectors. Differences in hours worked appear to be substantial in Finance and Business Services. Country-specific values for α have a non–negligible effect on *success* in Construction, Distribution Services, and Finance and Business Services. Overall, *success* is quite robust in Manufacturing, Personal Services, and also Distribution Services across the different specifications in panel A. Conversely, factor endowments can explain between less than half and almost all of the output per worker variation in Construction, depending on how the labor input and α are measured.

Panel B of Table 3 shows the *success* values for the specifications in which different labor types are imperfect substitutes in production, but physical and human capital still enter a Cobb-Douglas production function. In line with the results for the aggregate Market sector, *success* increases substantially in all subsectors. Yet, it is worth noticing that less so in Manufacturing. In Finance and Business Services and Construction, *success* even exceeds the value of one.

The sectoral results for the the appropriate technology framework with a CES production function are shown in panel C of table 3, columns (2)-(6). Recall that physical and human capital are estimated gross complements in all sectors. As in the Market sector, imposing the estimated σ_i leads to an increase in *success*, particularly in Distribution Services, Manufacturing, and Finance and Business Services. Hence, the appropriate technology CES framework contributes a smaller fraction of the cross-country variation in output per worker to barriers in technology adoption. The Finance and Business Services represents a distinct case as the *success* values are above two.[30] Note that rows (10) and (12) suggest that the relative efficiency channel is still relevant if we assume that skill types are imperfect substitutes and the aggregate human capital input is complementary to physical capital. Finally, row (13) shows that the qualitative differences across sectors are not driven by specific frontier technologies.

Table 9 checks the robustness of our results with respect to single outliers. Some differences between *success* and $success^{90/10}$ exist, but the results seem to be qualitative the same,

[30] This suggests that the large value of *success* for the aggregate Market sector in the CES specification is driven by Finance and Business Services.

and also quantitative quite similar. What is notable is a substantially larger value in Personal Services in the specification with human capital, shown in row (3). Not surprising, the role of barriers to technology adoption in the sector is also revised downwards in the Cobb-Douglas specification with imperfect substitution (rows (6) and (7)). This can be explained by the fact that the positive relationship between output per worker and technology levels is less clear at higher output per worker levels. The opposite is the case in Finance and Business Services. Here, the role of barriers to technology adoption is revised upwards. However, contrary to Personal Services, the qualitative findings do not change. Regarding the results based on the appropriate technology framework, *success* and $success^{90/10}$ are remarkable similar in Distribution Services and Manufacturing, while some differences exist in Construction and Personal Services. The inter-percentile ratio revises the explanatory power of barrier to technology upwards in the former, but downwards in Personal Services. However, across specifications, the results of *success* and $success^{90/10}$ are consistent.

Our sector-level results reiterate the sensitivity of development accounting with regard to the production function specification and parameter values imposed. Another robust finding is the reduced explanatory power of barrier to technology adoption, once technology is assumed to be factor-specific and assumptions on the substitutability of inputs are relaxed. Finally, our sector-level results also confirm the finding for the aggregate Market sector that the fraction in output per worker variation explained by barriers to technology adoption further decrease if frontier technologies are geared towards the input factor mix of countries with high physical capital per worker. This is evidenced in appendix table 16 showing that higher output per worker corresponds to lower levels of A_K and higher levels of A_H across sectors, except for manufacturing. This confirms Caselli's (2005) finding that rich countries use human capital more efficiently but physical capital less efficiently compared to poor countries for the sector level. What is driving this result is the fact that output per worker is negatively correlated with the h/k-ratio. Since physical and human capital are estimated to be gross complements in all sectors, it is reasonable for countries to opt for technologies that augment the relatively scarce factor.

6.3 Discussion of sector differences: manufacturing vs. finance

From a macroeconomic development perspective, it is important to not only understand which sectors make countries less productive (Herrendorf and Valentinyi, 2012) but also *why* sectoral productivity differences emerge. Our results have demonstrated substantial differences across sectors. Notably, barriers to technology adoption play only a minor or no role in explaining cross-country output per worker differences in Finance and Business Services and in Distribution Services but they can account for a substantial fraction (30-40%)

in the output per worker variation in Manufacturing and Personal Services. We therefore focus on the two sectors with quite robust but contrasting findings: Manufacturing and Finance and Business Services to highlight key differences in production technologies.

A first point worth stressing is that differences in *success* ratios across both sectors are not due to differences in factor accumulation per se. This can be inferred from appendix table 15 which shows that the correlation between $ln(k)$ and $ln(y)$ is weaker in Finance and Business Services than in Manufacturing. And somewhat surprisingly, there even is a negative correlation between $ln(h)$ and $ln(y)$ in the former sector.[31] Instead, appendix table 15 suggests that the large fraction in the output per worker variation explained by factor endowments in Finance and Business Services is due to a negative correlation between the factor endowments and the productivity term A (in the Cobb-Douglas setup). That is, countries that employ more physical and human capital inputs per worker in this sector do utilize these inputs less efficiently. Imposing the same efficiency level A across countries thus raises the output of those inefficient, but factor abundant, countries in particular. For Manufacturing, in contrast, appendix table 15 shows that countries endowed with more physical capital per worker have, on average, also higher productivity levels. As a consequence, eliminating technology differences considerably decreases the variation in output per worker across countries, which explains the lower *success* value.[32] Note that the negative correlation between $ln(h)$ and $ln(A)$ increases with imperfect substitution across skill types in both sectors ($\eta = 4$, panel (3) of table 15). Hence, countries that are endowed with high human capital per worker levels benefit particularly from removing technology differences.

Our appropriate technology CES framework substantiates the insights about the relationship between factor endowments and productivity for Finance and Business Services in three notable ways. First, the stocks of physical and human capital per worker are quite strongly negatively correlated with their respective factor-specific efficiency parameters (table 16). Second, examining the assigned technology combinations reveals that countries tend to adopt a technology combination that increases A_H, both absolutely and relatively to A_K.[33] This indicates that effective human capital is relatively scarce, while physical capital is used relatively unproductively in Finance and Business Services. And third, the global technology menu in Finance and Business Services contains several technology combination that

[31] This holds regardless of whether we calculate h in per worker or per hours worked terms. The reason for the negative correlation are the high skill efficiency levels in Finance and Business Services in poorer countries. As a consequence, there is also a negative correlation between the endowment of physical and human capital in Finance and Business Services.

[32] Note that in neither case, countries with higher output per worker are systematically less productive: the correlation between $ln(y)$ and $ln(A)$ is still moderately positive.

[33] In the baseline setting all countries adopt a technology combination that increases A_H/A_K. When we withhold the three most appropriate technology combinations for each country, 75% of the countries adopt a technology combination that increases A_H/A_K.

greatly enhances human capital. Taken together, these correlations suggests that the benefit of accessing appropriate *factor-specific* technologies are, on average, particularly large for countries with larger physical capital per worker levels. Indeed, this is was table 16 shows.

We can contrast this finding with the relatively low *success* values in Manufacturing. Recall that the Cobb-Douglas results suggested a strong positive correlation between the physical capital stock per worker and a countries technology A. Table table 16 reveals that it is in fact the efficiency with which countries employ human capital that correlates strongly with a countries level of output and physical capital used per worker. Note that this indicates that those countries are able to remedy the output losses associated with an unfavorable input mix. By using technologies that increases the effective input of human capital, these countries can make productive use of their abundance in physical capital per worker. And indeed, also in Manufacturing, the technology frontier is represented by technology combinations of advanced countries that greatly augment human capital relative to physical capital. Applying the same logic as before, this particularly benefits countries that are quite abundant in physical capital, which tend to be again countries that produce more output per worker. Note, however, that this also suggests that the potential output gains associated to accessing the global menu of technology combinations is rather limited in these countries as their technology is already geared to their input factor mix. This is an important difference compared to the situation in Finance and Business Services. Consequently, the variation in $ln(y_{hyp})$ is smaller than in $ln(y)$.

All things considered, the development accounting exercise on the sector level leads to four main findings. First, development accounting is sensitive to the production function specification and parameter values imposed. Second, across sectors, productivity differences can largely be pinned down to the efficiency with which human capital is used. Third, to what extent cross-country variation in output per worker can be explained by factor endowments relative to barriers to technology adoption differs substantially across sectors. This emphasizes the importance of complementing development accounting on the country level with sector-level analyses based on different specifications to provide better orientation for economic theory and policy making.

7 Conclusion

Development accounting on the sector level can help to better understand the proximate causes of why some countries produce so much more output per worker than others. However, for long, the lack of internationally comparable output prices and sectoral inputs has been a major bottleneck for such kind of analysis. This paper combined data from WIOD-SEA with multilateral relative industry-level prices to perform a development accounting exercise on the sector level for a sample of 38 countries.

On top of the standard Cobb-Douglas specification, we considered more flexible production functions, notably the appropriate technology framework proposed by Caselli (2005), where skill types may be imperfect substitutes, technology can be factor-specific, and sectoral elasticities of substitution between physical and human capital are empirically estimated. Our estimation results of this elasticity of substitution in the range of 0.4 to 0.6 in all sectors suggests that the standard Cobb-Douglas specification is too restrictive and a CES specification is more appropriate.

A key high-level takeaway of our exercise is that the standard notion of '*total* factor productivity' explaining the key part of cross-country income differences in market sectors is empirically implausible. Once we consider production factors to be less substitutable than in the neoclassical Cobb-Douglas workhorse specification, factor endowments and the efficiency of human capital use play a much larger role. Our discussion of secor differences between manufacturing and finance and business services highlighted the complex interplay between factor endowment structures and factor-specific efficiencies to understand sectoral output per worker differences across countries. Our methodological approach and findings hence also add to important macroeconomic debates about directed technological change, skill bias, income distribution, and development (e.g., Acemoglu, 2002; Rodrik, 2018; Bergholt et al., 2022; Acemoglu and Johnson, 2023).

In current research, we further explore what our more flexible production structure implies for the potential gains of structural change (e.g., Duarte and Restuccia, 2010). Future research could also build on our approach to investigate to what extent the positive correlation between substitution elasticities and income levels that is typically found an the aggregate level reflects countries' different sectoral compositions (Duffy and Papageorgiou, 2000; Alvarez-Cuadrado et al., 2017). Our estimates suggest that differences in this elasticity across different market sectors are small but we had to neglect relevant non-market sectors due to data constraints. Our study hence also highlights potential benefits of further improving the quality and comparability of international sectoral data on output, inputs, and prices.

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Appendix

Appendix A: Additional Tables and Figures

Table 4: Country overview

isoc3	Country	isoc3	Country	isoc3	Country
AUS	Australia	FIN	Finland	LVA	Latvia
AUT	Austria	FRA	France	MEX	Mexico
BEL	Belgium	GBR	United Kingdom	NLD	Netherlands
BGR	Bulgaria	GRC	Greece	POL	Poland
BRA	Brazil	HUN	Hungary	PRT	Portugal
CAN	Canada	IND	India	ROU	Romania
CHN	China	IDN	Indonesia	RUS	Russia
CYP	Cyprus	IRL	Ireland	SVK	Slovak Republic
CZE	Czech Republic	ITA	Italy	SVN	Slovenia
DEU	Germany	JPN	Japan	SWE	Sweden
DNK	Denmark	KOR	South Korea	TUR	Turkey
ESP	Spain	LTU	Lithuania	USA	United States
EST	Estonia	LUX	Luxembourg		

Table 5: 1997 ISCED Classification

WIOD skill type	**ISCED level**	**1997 ISCED level description**
Low	-	No schooling
Low	1	Primary education or first stage of basic education
Low	2	Lower secondary or second stage of basic education
Medium	3	(Upper) secondary education
Medium	4	Post-secondary non-tertiary education
High	5	First stage of tertiary education
High	6	Second stage of tertiary education

The information on hours worked in WIOD-SEA includes both employees and self-employed. The latter is estimated based on the assumption that average hours worked by employees and self-employed are equal.

Table 6: Summary statistics of the data (2007)

Sector Abbr.	y				k				$hours$			
	Mean	sd.	Min.	Max.	Mean	sd.	Min.	Max.	Mean	sd.	Min.	Max.
Market	51,832	25,891	10,274	115,5	68,543	51,095	4,710	214,067	1,831	259	1,334	2,454
Const	37,716	15,773	10,055	61,879	29,027	27,675	1,217	127,518	1,907	276	1,065	2,401
Distrib	50,216	24,028	6,19	111,423	84,779	66,12	3,967	227,105	1,851	271	1,339	2,55
FinBus	71,006	30,398	22,949	164,812	66,772	50,589	7,212	232,417	1,825	259	1,401	2,459
Manu	68,671	47,109	8,503	205,354	89,289	71,536	6,138	326,418	1,854	266	1,238	2,407
Pers	30,84	13,159	3,294	53,143	50,317	43,532	2,671	159,477	1,758	311	1,11	2,51
	h				$\frac{h_c^{LM}}{h_c^{\tilde{L}L}}$				$\frac{h_c^{LH}}{h_c^{\tilde{L}L}}$			
	Mean	sd.	Min.	Max.	Mean	sd.	Min.	Max.	Mean	sd.	Min.	Max.
Market	13.5	3.4	6.4	21.6	2.7	0.6	1.8	5.4	4.8	1.5	2.4	8.7
Const	12.4	3.3	4.7	19.7	2.5	0.5	1.8	4.5	4.3	1.6	2.6	10.5
Distrib	12.9	3.1	5.9	19.8	2.6	0.6	1.6	4.5	4.5	1.3	2.0	8.6
FinBus	18.4	6.1	10.1	31.9	3.1	0.8	1.7	5.8	5.2	1.9	2.4	11.3
Manu	13.1	3.7	5.3	25.5	2.7	0.5	2.0	4.7	4.7	1.5	2.8	9.3
Pers	12.4	3.0	6.5	20.4	2.7	0.6	1.8	5.1	4.5	1.4	1.8	8.2
	LL				LM				LH			
	Mean	sd.	Min.	Max.	Mean	sd.	Min.	Max.	Mean	sd.	Min.	Max.
Market	30.6	22.2	2.9	76.1	51.1	18.7	17.7	83.5	18.3	8.4	6.1	43.5
Const	39.1	28.2	3.7	88.6	50.7	24.9	8.8	89.4	10.3	9.5	2.5	58.0
Distrib	29.2	21.9	2.6	70.4	55.7	19.2	23.3	87.6	15.1	8.6	4.6	46.9
FinBus	13.9	9.8	0.5	36.1	45.0	10.8	22.7	67.3	41.1	10.9	14.8	62.4
Manu	33.9	24.0	4.4	83.0	51.5	20.7	12.9	86.4	14.6	8.3	3.4	32.9
Pers	33.1	23.4	3.2	80.3	49.7	19.3	15.0	84.0	17.2	8.4	3.8	37.0

Note: y, k, and hours are per worker levels of value added, physical capital, and hours worked. h is human capital per hour worked. LL, LM, and LH are the skill fractions in total hours worked. $\frac{h_c^{LM}}{h_c^{\tilde{L}L}}$ and $\frac{h_c^{LH}}{h^{\tilde{L}L}}$ are country-specific relative efficiency levels for the case of perfect substitution.

Table 7: Correlation matrix for Market sector values (2007)

	$ln\,(y)$	$ln\,(k)$	$ln\,(hours)$	$ln\,(h)$	$ln\left(\frac{h_c^{LM}}{h_c^{LL}}\right)$	$ln\left(\frac{h_c^{LH}}{h_c^{LL}}\right)$	$ln\,(h_{alt})$	LL	LM	LH
$ln\,(y)$	1.00									
$ln\,(k)$	0.90	1.00								
$ln\,(hours)$	-0.40	-0.43	1.00							
$ln\,(h)$	0.48	0.41	-0.06	1.00						
$ln\left(\frac{h_c^{LM}}{h_c^{LL}}\right)$	0.11	0.06	0.03	0.66	1.00					
$ln\left(\frac{h_c^{LH}}{h_c^{LL}}\right)$	-0.38	-0.32	0.24	0.34	0.70	1.00				
$ln\,(h_{alt})$	0.68	0.61	-0.20	0.66	-0.07	-0.42	1.00			
LL	-0.40	-0.33	0.06	-0.63	0.04	0.13	-0.80	1.00		
LM	0.20	0.13	0.00	0.57	0.02	0.07	0.59	-0.92	1.00	
LH	0.59	0.56	-0.16	0.38	-0.15	-0.47	0.77	-0.55	0.19	1.00

Note: y, k, and hours are per worker levels of value added, physical capital, and hours worked. h is human capital per hour worked with country-specific relative efficiency terms. h_{alt} is human capital per hour worked with common relative efficiency terms. LL, LM, and LH are the skill fractions in total hours worked. $\frac{h^{LM}}{h^{LL}}$ and $\frac{h^{LH}}{h^{LL}}$ are country-specific relative efficiency levels.

Table 8: Estimates for the Market sector

	Specification	σ	$90\% - CI$	α	ν	ν_K	ν_H
(1)	PF pooled neutral	0.60	(1.03-0.42)		0.01		
(2)	PF pooled directed	0.64	(1.05-0.46)			-0.06	0.09
(3)	PF FE neutral	0.49	(0.62-0.41)		0.01		
(4)	PF FE directed	0.45	(0.65-0.35)			0.01	0.01
(5)	PF FE directed $\hat{\alpha}$	0.42	(0.67-0.30)	0.35		0.01	0.01
(6)	NLSUR pooled neutral	0.57	(0.62-0.53)		0.02		
(7)	NLSUR pooled directed	0.50	(0.53-0.48)			0.01	0.01
(8)	NLSUR FE neutral	0.49	(0.52-0.45)		0.02		
(9)	NLSUR FE directed	0.49	(0.53-0.46)			0.03	0.02
(10)	NLSUR FE directed $\hat{\alpha}$	0.58	(0.61-0.55)	0.57		0.00	0.02

Note: Estimates of elasticities of substitution between physical capital and human capital, σ, in the Market sector based on different imposed values of η. α represents the capital share and is set to 0.41 if not estimated. ν, ν_K, and ν_H represent neutral, capital-, and labor-directed technical change, respectively. Specifications: *PF:* Normalized production function only. *NLSUR:* Two-step FGNLSUR on a normalized supply side system. *pooled:* All observations pooled. *FE:* country-fixed effects included. N = 494. Estimates rounded to two digits.

Table 9: $success^{90/10}$ ratios for different specifications (2007)

		(1) Market	(2) Const	(3) Distrib	(4) FinBus	(5) Manu	(6) Pers
Panel A: Cobb-Douglas with perfect substitution							
(1)	with common α and L	0.49	0.61	0.63	0.75	0.44	0.49
(2)	with α and raw hours worked	0.47	0.58	0.61	0.62	0.36	0.50
(3)	with α and H	0.57	0.66	0.70	0.84	0.40	0.67
(4)	with α and H_{alt}	0.58	0.69	0.72	0.73	0.45	0.57
(5)	with H and country-specific α_c	0.54	0.65	0.62	0.73	0.45	0.59
Panel B: Cobb-Douglas with imperfect substitution of skill types							
(6)	with α and $\eta = 4$	0.70	0.99	0.95	1.00	0.57	0.83
(7)	with α_c and $\eta = 4$	0.72	1.07	0.95	1.19	0.59	0.89
(8)	with H_{alt}, α, and $\eta = 4$	0.60	0.74	0.76	0.73	0.45	0.57
Panel C: CES with (im)perfect substitution of skill types							
(9)	with H	0.83	0.64	0.92	1.40	0.67	0.65
(10)	with H and $\eta = 4$	0.80	1.00	1.16	1.35	0.73	0.85
(11)	with H_{alt}	0.99	0.55	0.86	1.39	0.69	0.59
(12)	with H_{alt} and $\eta = 4$	0.78	0.60	0.90	1.39	0.70	0.61
(13)	with H and adjusted frontier	0.70	0.64	0.86	1.18	0.64	0.73

Note: $success^{90/10}$ relates the 90th-to-10th percentile output per worker ratio of the counterfactual world to the actual value. α is set to 0.41 in Market; 0.34 in Const; 0.43 in Distrib; 0.45 in FinBus; 0.44 in Manu; and 0.32 in Pers. H_{alt} uses common relative efficiency levels. σ is set to 0.49 in Market; 0.45 in Const; 0.53 in Distrib; 0.57 in FinBus; 0.52 in Manu; and 0.46 in Pers.

Table 10: Relative efficiencies for different elasticities of substitution

isoc3	$\left(\frac{h_{ci}^{HM}}{h_{ci}^{\tilde{LL}}}\right)^{\gamma}$ and $\left(\frac{h_{ci}^{LM}}{h_{ci}^{\tilde{LL}}}\right)^{\gamma}$							
	$\gamma \to 1$, $\eta \to \infty$		$\gamma \to 0.75$, $\eta \to 4$		$\gamma \to 0.5$, $\eta \to 2$		$\gamma \to 0.375$, $\eta \to 1.6$	
Common	4.6	2.7	3.4	2.6	2.5	2.5	2.1	2.5
AUT	4.2	2.6	3.2	3.1	2.4	3.6	2.1	3.9
BEL	3.4	2.3	2.4	2.2	1.7	2.1	1.4	2.1
BGR	5.1	2.6	2.2	1.5	0.9	0.9	0.6	0.7
BRA	8.7	2.7	5.0	2.1	2.8	1.7	2.1	1.5
CAN	4.3	3.1	5.2	5.3	6.1	9.2	6.7	12.2
CHN	2.4	1.8	1.3	1.6	0.7	1.5	0.5	1.4
CYP	3.3	2.2	2.6	2.0	2.1	1.8	1.8	1.7
CZE	5.0	2.4	4.7	3.8	4.5	6.0	4.3	7.5
DEU	4.7	2.7	4.2	3.2	3.7	3.8	3.5	4.2
DNK	3.6	2.9	3.0	3.0	2.4	3.1	2.2	3.1
ESP	3.1	2.2	2.1	1.5	1.5	1.0	1.2	0.8
EST	4.9	2.8	5.0	3.5	5.2	4.3	5.2	4.8
FIN	3.0	2.2	2.6	2.1	2.2	2.1	2.0	2.1
FRA	3.5	2.1	2.8	2.0	2.2	1.9	2.0	1.9
GBR	4.5	2.8	3.4	2.6	2.6	2.4	2.2	2.3
GRC	3.4	2.0	2.3	1.8	1.6	1.6	1.3	1.5
HUN	6.6	2.5	5.4	3.1	4.4	3.8	3.9	4.2
IND	5.6	2.5	2.7	1.7	1.3	1.2	0.9	1.0
IDN	6.4	2.6	3.6	2.1	2.0	1.7	1.5	1.5
IRL	3.6	2.6	2.8	2.3	2.1	2.1	1.9	2.0
ITA	3.8	2.5	2.1	2.0	1.1	1.6	0.8	1.4
JPN	3.8	2.4	3.8	3.2	3.7	4.1	3.7	4.7
KOR	3.6	2.4	3.8	2.8	4.1	3.2	4.3	3.4
LTU	3.4	2.0	3.9	3.0	4.6	4.3	4.9	5.3
LUX	4.2	2.9	2.9	2.4	2.1	2.1	1.7	1.9
LVA	4.2	2.2	3.9	2.8	3.6	3.6	3.5	4.0
MEX	8.6	5.4	5.1	4.5	3.0	3.8	2.3	3.5
NLD	4.1	2.9	3.0	2.6	2.2	2.3	1.9	2.1
POL	6.1	3.0	5.6	4.3	5.1	6.2	4.9	7.4
PRT	5.7	2.9	2.5	1.7	1.1	1.0	0.7	0.7
ROU	5.4	2.9	2.3	1.6	1.0	0.9	0.6	0.7
RUS	6.8	2.6	6.3	4.1	5.8	6.5	5.5	8.2
SVK	5.1	2.6	5.1	4.3	5.1	7.2	5.1	9.3
SVN	6.6	3.1	5.4	3.8	4.5	4.5	4.0	5.0
SWE	3.7	2.5	2.8	2.7	2.1	2.8	1.8	2.9
TUR	5.4	2.5	2.9	1.7	1.5	1.1	1.1	0.9
USA	7.1	3.8	6.7	4.5	6.3	5.3	6.1	5.8

Note: See equation 23 and equation 24 for details on calculation of $\left(\frac{h_{ci}^{LM}}{h_{ci}^{LL}}\right)$ and $\left(\frac{h_{ci}^{LH}}{h_{ci}^{LL}}\right)$. The elasticity of substitution between the skill types is defined as $\eta = 1/(1-\gamma) > 0$. Common is calculated as in equation 26 and equation 27.

Table 12: Human capital input for different elasticities of substitution

isoc3	human capital per worker							
	with country-specific skill efficiency terms				with homogeneous skill efficiency terms			
	$\gamma \to 1$	$\gamma \to 0.75$	$\gamma \to 0.5$	$\gamma \to 0.375$	$\gamma \to 1$	$\gamma \to 0.75$	$\gamma \to 0.5$	$\gamma \to 0.375$
	$\eta \to \infty$	$\eta \to 4$	$\eta \to 2$	$\eta \to 1.6$	$\eta \to \infty$	$\eta \to 4$	$\eta \to 2$	$\eta \to 1.6$
AUS	9.9	13.5	25	46.1	8.4	13.7	37.6	104.4
AUT	7.5	14.5	54.3	203.2	7.7	12.9	35.8	100.1
BEL	6.8	10.6	25.4	61.2	7.9	13.3	37.3	104.9
BGR	5.7	6.4	8.1	10.4	5.6	8.4	21.2	56.7
BRA	5.8	8.3	17.1	35.4	4.8	8	22.3	62.3
CAN	9	30.2	338.4	3788.2	8.3	13.3	35.2	95.2
CHN	4.9	6.5	11.5	20.4	6.5	10.7	29.6	82.7
CYP	6.1	9.4	22.5	53.8	7.4	12.3	34.2	95.8
CZE	7.4	20.1	147.7	1084.7	7.9	12.6	33.4	91.1
DEU	8.1	17	75.6	336.5	7.9	13.1	36.5	102
DNK	7.9	14.2	45.8	148.5	8.2	13.6	38	106.6
ESP	6	7.7	12.8	21.3	7.3	11.8	31.6	87
EST	9.5	22.3	123.6	685.1	9	14.8	40.6	113
FIN	6.7	11.2	31.2	87	8.7	14.3	39.8	111.4
FRA	6.7	10.7	27.5	70.8	8.2	13.5	37.6	105.3
GBR	8.4	13.9	38.1	104.5	8.3	13.8	38.6	108.4
GRC	5.7	8.2	16.8	34.7	7	11.6	32.6	91.7
HUN	8.5	18	81.8	371.9	7.9	13	36	100.3
IND	4.8	5.9	8.9	13.4	4.7	7.6	20.7	57.4
IDN	5.8	8.2	16.1	31.6	5.5	9	25	69.9
IRL	7.5	11.8	29.8	75	8.3	13.8	38.2	106.9
ITA	6.5	8.6	15.2	27	6.8	11.3	31.3	87.6
JPN	8	18.1	93.2	479.1	9	14.8	40.3	111.3
KOR	8.4	18.1	83.8	389.4	10	15.9	42	114.6
LTU	6.2	15.8	101.9	658.3	8.1	13.2	35.4	97.2
LUX	7.4	11.3	26.2	61	7.4	12.3	34.5	96.6
LVA	6.7	14.5	66.7	307.8	7.7	12.8	35.2	98.2
MEX	9.6	16.1	45	126	5.7	9.4	26.3	73.7
NLD	8.5	13.4	33.2	82.4	8.5	14.1	39.4	110.5
POL	9.3	24.2	165.4	1131.2	7.8	12.7	34.6	95.3
PRT	6	6.9	9.1	12.1	5.6	8.6	22	59.3
ROU	6	6.8	8.7	11.2	5.8	8.6	21.6	57.4
RUS	8.1	22.6	177.6	1395.5	7.5	11.9	31.5	85.7
SVK	7.9	23.5	207	1822.4	7.9	12.6	33.2	89.9
SVN	10	21.8	104.6	502	8	13.3	36.9	103.1
SWE	7.4	12.9	39.4	120.5	8.1	13.5	37.9	106.4
TUR	5.2	6.4	10	15.7	5.1	8.2	22.1	61
USA	12	28.9	168.9	986.7	8.4	13.9	38.5	107.5

Note: The elasticity of substitution between the skill types is defined as $\eta = 1/(1-\gamma) > 0$.

Table 13: Correlation matrix for Market sector values

	$ln(h)$				$ln(h_{alt})$			
	$\eta \to \infty$	$\eta \to 4$	$\eta \to 2$	$\eta \to 1.6$	$\eta \to \infty$	$\eta \to 4$	$\eta \to 2$	$\eta \to 1.6$
$ln(y)$	0.19	0.21	0.20	0.20	0.33	0.37	0.40	0.41

Note: $ln(y)$ is output per worker. $ln(h)$ and $ln(h_{alt})$ are human capital per worker for different elasticities of substitution across skill types.

Table 15: Correlation matrix for sectors (Cobb-Douglas scenario, 2007)

	Financial and Business Services						*Manufacturing*				
	$ln\,(y)$	$ln(A)$	$ln\,(k)$	$ln\,(h)$	$\triangle ln\,(y)$		$ln\,(y)$	$ln(A)$	$ln\,(k)$	$ln\,(h)$	$\triangle ln\,(y)$
Panel (1)											
$ln\,(y)$	1.00					$ln\,(y)$	1.00				
$ln(A)$	0.53	1.00				$ln(A)$	0.90	1.00			
$ln\,(k)$	0.56	-0.41	1.00			$ln\,(k)$	0.88	0.58	1.00		
$ln\,(h)$	.	.	.	.		$ln\,(h)$	.	.	.	.	
$\triangle ln\,(y)$	-0.47	-0.97	0.44	.	1.00	$\triangle ln\,(y)$	-0.83	-0.95	-0.51	.	1.00
Panel (2)											
$ln\,(y)$	1.00					$ln\,(y)$	1.00				
$ln(A)$	0.59	1.00				$ln(A)$	0.84	1.00			
$ln\,(k)$	0.56	-0.26	1.00			$ln\,(k)$	0.88	0.52	1.00		
$ln\,(h)$	-0.34	-0.55	-0.21	1.00		$ln\,(h)$	0.24	-0.11	0.20	1.00	
$\triangle ln\,(y)$	-0.51	-0.95	0.29	0.53	1.00	$\triangle ln\,(y)$	-0.76	-0.95	-0.44	0.11	1.00
Panel (3)											
$ln\,(y)$	1.00					$ln\,(y)$	1.00				
$ln(A)$	0.57	1.00				$ln(A)$	0.74	1.00			
$ln\,(k)$	0.56	-0.14	1.00			$ln\,(k)$	0.88	0.47	1.00		
$ln\,(h)$	-0.30	-0.71	-0.24	1.00		$ln\,(h)$	0.24	-0.32	0.18	1.00	
$\triangle ln\,(y)$	-0.49	-0.94	0.19	0.65	1.00	$\triangle ln\,(y)$	-0.70	-0.96	-0.41	0.28	1.00

Note: y, k, and h are per worker levels of value added, physical capital, and human capital. $\triangle ln\,(y)$ is the output per worker growth rate. In panel (1): Labor input is number of workers. In (2): $\eta = \infty$. In (3): $\eta = 4$. A is the total factor productivity term.

Table 16: Correlation matrix for sectors (CES scenario, 2007)

	$ln\,(y)$	$ln(A_K)$	$ln(A_H)$	$ln\,(k)$	$ln\,(h)$	$\triangle ln\,(y)$		$ln\,(y)$	$ln(A_K)$	$ln(A_H)$	$ln\,(k)$	$ln\,(h)$	$\triangle ln\,(y)$
			Market Sector							*Construction*			
$ln\,(y)$	1.00						$ln\,(y)$	1					
$ln(A_K)$	-0.31	1.00					$ln(A_K)$	-0.17	1.00				
$ln(A_H)$	0.84	-0.32	1.00				$ln(A_H)$	0.69	-0.36	1.00			
$ln\,(k)$	0.90	-0.64	0.71	1.00			$ln\,(k)$	0.77	-0.66	0.52	1.00		
$ln\,(h)$	0.19	0.09	-0.28	0.11	1.00		$ln\,(h)$	0.23	0.03	-0.43	0.23	1.00	
$\triangle ln\,(y)$	-0.26	-0.63	-0.48	0.13	0.26	1.00	$\triangle ln\,(y)$	-0.51	-0.34	-0.69	-0.03	0.44	1
			Distribution Services							*Financial and Business Services*			
$ln\,(y)$	1.00						$ln\,(y)$	1.00					
$ln(A_K)$	-0.47	1.00					$ln(A_K)$	-0.12	1.00				
$ln(A_H)$	0.83	-0.48	1.00				$ln(A_H)$	0.71	-0.13	1.00			
$ln\,(k)$	0.88	-0.75	0.68	1.00			$ln\,(k)$	0.56	-0.68	0.15	1.00		
$ln\,(h)$	0.24	0.14	-0.12	0.05	1.00		$ln\,(h)$	-0.34	0.05	-0.67	-0.21	1.00	
$\triangle ln\,(y)$	-0.33	-0.47	-0.51	0.10	-0.03	1.00	$\triangle ln\,(y)$	-0.16	-0.73	-0.41	0.65	0.25	1.00
			Manufacturing							*Personal Services*			
$ln\,(y)$	1.00						$ln\,(y)$	1.00					
$ln(A_K)$	0.14	1.00					$ln(A_K)$	-0.25	1.00				
$ln(A_H)$	0.88	0.11	1.00				$ln(A_H)$	0.88	-0.28	1.00			
$ln\,(k)$	0.88	-0.28	0.71	1.00			$ln\,(k)$	0.81	-0.66	0.63	1.00		
$ln\,(h)$	0.24	-0.01	-0.13	0.20	1.00		$ln\,(h)$	0.16	0.09	-0.25	0.10	1.00	
$\triangle ln\,(y)$	-0.54	-0.79	-0.62	-0.11	0.09	1.00	$\triangle ln\,(y)$	-0.76	-0.05	-0.89	-0.39	0.29	1.00

Note: y, k, and h are per worker levels of value added, physical capital, and human capital. $\triangle ln\,(y)$ is the output per worker growth rate. A_K and A_H are the current factor-specific productivity terms.

Table 11: Correlation matrix for Market sector values

						$ln\left(\frac{h_c^{LH}}{h_c^{LL}}\right)$				$ln\left(\frac{h_c^{LM}}{h_c^{LL}}\right)$			
		$ln(y)$	LH	LM	LL	$\eta \to \infty$	$\eta \to 4$	$\eta \to 2$	$\eta \to 1.6$	$\eta \to \infty$	$\eta \to 4$	$\eta \to 2$	$\eta \to 1.6$
	$ln(y)$	1.00											
	LH	0.59	1.00										
	LM	0.20	0.19	1.00									
	LL	-0.40	-0.55	-0.92	1.00								
$ln\left(\frac{h_c^{LH}}{h_c^{LL}}\right)$	$\eta \to \infty$	-0.38	-0.47	0.07	0.13	1.00							
	$\eta \to 4$	-0.01	0.11	0.67	-0.62	0.68	1.00						
	$\eta \to 2$	0.19	0.40	0.82	-0.85	0.33	0.92	1.00					
	$\eta \to 1.6$	0.23	0.47	0.83	-0.89	0.23	0.88	0.99	1.00				
$ln\left(\frac{h_c^{LM}}{h_c^{LL}}\right)$	$\eta \to \infty$	0.11	-0.16	0.01	0.05	0.70	0.50	0.26	0.20	1.00			
	$\eta \to 4$	0.23	0.20	0.85	-0.80	0.37	0.86	0.90	0.88	0.50	1.00		
	$\eta \to 2$	0.21	0.27	0.94	-0.91	0.20	0.80	0.92	0.92	0.25	0.96	1.00	
	$\eta \to 1.6$	0.21	0.28	0.95	-0.92	0.16	0.78	0.91	0.92	0.19	0.95	1.00	1.00

Note: LL, LM, and LH are the skill fractions in total hours worked. $\frac{h^{LM}}{h^{LL}}$ and $\frac{h^{LH}}{h^{LL}}$ are relative efficiency levels for different elasticities of substitution between skill types.

Table 14: Overview industry prices levels, 2005

Description	Code	mean	s.d.	min	max
Food, Beverages and Tobacco	15t16	0.71	0.22	0.33	1.27
Textiles and Textile Products	17t18	0.53	0.10	0.27	0.93
Leather, Leather and Footwear	19	0.51	0.08	0.27	0.74
Wood and Products of Wood and Cork	20	0.70	0.13	0.40	0.95
Pulp, Paper, Paper , Printing and Publishing	21t22	0.84	0.25	0.27	1.40
Coke, Refined Petroleum and Nuclear Fuel	23	0.88	0.20	0.35	1.21
Chemicals and Chemical Products	24	0.81	0.19	0.21	1.19
Rubber and Plastics	25	0.80	0.24	0.21	1.85
Other Non-Metallic Mineral	26	0.61	0.25	0.34	1.85
Basic Metals and Fabricated Metal	27t28	0.72	0.17	0.33	1.04
Machinery, Nec	29	0.69	0.08	0.51	0.87
Electrical and Optical Equipment	30t33	0.67	0.12	0.37	0.91
Transport Equipment	34t35	0.76	0.12	0.30	0.88
Manufacturing, Nec; Recycling	36t37	0.70	0.12	0.43	0.93
Sale, Maintenance and Repair of Motor Vehicles and Motorcycles; Retail Sale of Fuel	50	0.81	0.31	0.23	1.63
Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles	51	0.76	0.10	0.49	1.00
Retail Trade, Except of Motor Vehicles and Motorcycles; Repair of Household Goods	52	0.79	0.24	0.32	1.26
Inland Transport	60	0.84	0.48	0.26	2.02
Water Transport	61	0.78	0.48	0.20	2.48
Air Transport	62	1.16	0.42	0.47	2.59
Other Supporting and Auxiliary Transport Activities; Activities of Travel Agencies	63	0.74	0.35	0.27	1.66
Post and Telecommunications	64	0.85	0.24	0.23	1.23
Renting of M&Eq and Other Business Activities	71t74	0.79	0.25	0.34	1.29
Construction	F	0.82	0.39	0.25	1.74
Hotels and Restaurants	H	0.79	0.29	0.30	1.48
Financial Intermediation	J	0.79	0.25	0.36	1.32
Other Community, Social and Personal Services	O	0.75	0.36	0.24	1.56
Private Households with Employed Persons	P	1.09	0.64	0.15	2.49

Note: Price levels relative to the aggregate price level of the U.S. in 2005. *Data source:* Inklaar and Timmer (2014).

Appendix B: Details on human capital

B.1: Discussion of equation (11)

There is a merit to rewrite equation (11) as

$$H_{ci} = Q_{ci} h_{ci}^{LL} LL_{ci} \left[1 + \left(\frac{h_{ci}^{LM}}{h_{ci}^{LL}} \right)^{\gamma_i} \left(\frac{LM_{ci}}{LL_{ci}} \right)^{\gamma_i} + \left(\frac{h_{ci}^{LH}}{h_{ci}^{LL}} \right)^{\gamma_i} \left(\frac{LH_{ci}}{LL_{ci}} \right)^{\gamma_i} \right]^{\frac{1}{\gamma_i}} \tag{18}$$

For one, equation (18) clearly states that H_{ci} not only draws on information on *relative* efficiencies, but also contains h_{ci}^{LL}, which measures the contribution of low-skilled workers to human capital services in sector i in country c. In development accounting, LL is generally defined as workers with no educational attainment. It is then often (implicitly) assumed that h_{ci}^{LL} is equal across countries (see, e.g., Jones, 2014). One reason for this assumption is a lack of information in the data or literature from which to derive h_{ci}^{LL}. We will come back to this issue when we describe the construction of H_{ci} in the next section.

Further, equation (18) highlights two distinct implications of allowing skill types to be imperfect substitutes. First, the relative supply effect, captured by cross-country differences in $\left(\frac{LM_{ci}}{LL_{ci}}\right)^{\gamma_i}$ and $\left(\frac{LH_{ci}}{LL_{ci}}\right)^{\gamma_i}$. Second, the relative efficiency effect, captured by cross-country differences in $\left(\frac{h_{ci}^{LM}}{h_{ci}^{LL}}\right)^{\gamma_i}$ and $\left(\frac{h_{ci}^{LH}}{h_{ci}^{LL}}\right)^{\gamma_i}$. The relative efficiency terms are defined as

$$\left(\frac{h_{ci}^{LM}}{h_{ci}^{LL}} \right)^{\gamma} = \frac{w_{ci}^{LM}}{w_{ci}^{LL}} \left(\frac{LM_{ci}}{LL_{ci}} \right)^{1-\gamma} \tag{19}$$

$$\left(\frac{h_{ci}^{LH}}{h_{ci}^{LL}} \right)^{\gamma} = \frac{w_{ci}^{LH}}{w_{ci}^{LL}} \left(\frac{LH_{ci}}{LL_{ci}} \right)^{1-\gamma} \tag{20}$$

Note that in the traditional approach where $\gamma \to 1$ (i.e., perfect substitution), H_{ci} generates a measure of *low-skilled labor equivalents* by weighting the hours worked by each skill type with its relative efficiency, which is simply the relative wage.

Now consider the case of imperfect substitution, $0 < \gamma < 1$. The first implication is that cross-country differences due to the relative supply effect *decrease* with lower γ. Conversely, from equation (19) and equation (20) it follows that the relative efficiency channel *increases* human capital differences for lower values of γ. To explain this, note that in line with neoclassical predictions, relative wages are generally larger in poor countries due to lower relative supply of high- and medium-skilled workers. Hence, the relative efficiency channel generally decreases human capital differences in the case of perfect substitution (see e.g., Caselli, 2016). As γ decreases, however, cross-country differences in $\left(\frac{LM_{ci}}{LL_{ci}}\right)^{1-\gamma}$ and $\left(\frac{LH_{ci}}{LL_{ci}}\right)^{1-\gamma}$

increase and at some point dominate the relative wage term.[34] Intuitively, for lower levels of substitutability, the large differences in the relative skill supply are not reflected in the relative wage premia across countries. This suggests that the relative efficiency levels in skill abundant countries have to be larger than in low-skill abundant countries. In sum, by lowering the substitution elasticity between workers we increase the role of the relative efficiency channel, while we reduce the importance of the relative supply channel. This explains why the relative efficiency channel becomes important when one departs from the assumption of perfect substitution.

B.2: Details on skill inputs for human capital

In principle, WIOD-SEA thus provides all the information needed to obtain equation (14) but the broad classifications into three skill groups has weaknesses regarding the comparability of educational attainment and qualifications across countries. We thus augment the skill inputs indirectly using country information on the schooling attainment and duration. To be precise, we define

$$\tilde{LL}_{cit} = h_c^{LL} LL_{cit} \tag{21}$$

where h_c^{LL} is defined as

$$h_c^{LL} = exp\left[\phi_c \sum_{k=1}^{4} (\lambda_{ck} s_{ck})\right] \tag{22}$$

where ϕ capture the returns to schooling, λ is the percentage of people with schooling sub-levels k within the group with lower secondary education or less, and s represents the schooling duration up to each sub-level k. $\tilde{LL}_{cit}$ thus represents a measure of "*no-schooling* equivalents" that consists of workers with education levels ranging from "no schooling" to "some secondary schooling".[35]

Given $\tilde{LL}$, we can construct the relative efficiency terms based on the payment data included in WIOD-SEA to weight the *average* service flows of LM and LH. More precisely,

$$\left(\frac{h_{ci}^{LM}}{h_{ci}^{\tilde{LL}}}\right)^{\gamma} = \frac{w_{ci}^{LM}}{w_{ci}^{\tilde{LL}}}\left(\frac{LM_{ci}}{\tilde{LL}_{ci}}\right)^{1-\gamma} \tag{23}$$

[34]See Caselli and Coleman (2006) and Caselli and Ciccone (2019) for a more detailed explanation for why the relative efficiency gap increases when the elasticity of substitution across skill types declines.

[35]Note that the information on λ, s, and ϕ pertain to the aggregate country level, as sectoral information are not available.

$$\left(\frac{h_{ci}^{LH}}{h_{ci}^{\tilde{LL}}}\right)^{\gamma} = \frac{w_{ci}^{LH}}{w_{ci}^{\tilde{LL}}}\left(\frac{LH_{ci}}{\tilde{LL}_{ci}}\right)^{1-\gamma} \tag{24}$$

where the tildes in equation (23) and equation (24) refer to no-schooling equivalents. Appendix table 10 presents country-specific values for $\frac{h_i^{LM}}{h_i^{\tilde{LL}}}$ and $\frac{h_i^{LH}}{h_i^{\tilde{LL}}}$ for $\gamma = 1$.

As an alternative, we consider

$$H_{alt,cit} = Q_{ci}\tilde{LL}_{ci}\left[1 + \left(\frac{h_i^{LM}}{h_i^{\tilde{LL}}}\right)^{\gamma_i}\left(\frac{LM_{cit}}{\tilde{LL}_{cit}}\right)^{\gamma_i} + \left(\frac{h_i^{LH}}{h_i^{\tilde{LL}}}\right)^{\gamma_i}\left(\frac{LH_{cit}}{\tilde{LL}_{cit}}\right)^{\gamma_i}\right]^{\frac{1}{\gamma_i}} \tag{25}$$

with

$$\left(\frac{h_i^{LM}}{h_i^{\tilde{LL}}}\right)^{\gamma} = \frac{\bar{w}_i^{LM}}{\bar{w}_i^{LL}}\left(\frac{\bar{LM}_i}{\bar{\tilde{LL}}_i}\right)^{1-\gamma} \tag{26}$$

$$\left(\frac{h_i^{LH}}{h_i^{\tilde{LL}}}\right)^{\gamma} = \frac{\bar{w}_i^{LH}}{\bar{w}_i^{LL}}\left(\frac{\bar{LH}_i}{\bar{\tilde{LL}}_i}\right)^{1-\gamma} \tag{27}$$

where the bars in equation (26) and equation (27) refer to the geometric average over countries and years. Note that equation (25) eliminates the relative efficiency channel.

In order to augment each human capital measure with information on cross-country differences in schooling quality, we draw on the variable *cognitiveskills* from Caselli (2016). Specifically, we define $Q_c = exp\,(0.2 * cognitiveskills)$. The value of 0.2 follows Hanushek and Woessmann (2012) and Caselli (2016). The variable *cognitiveskills* summarizes scores from math and science tests from different PISA (Program for International Student Assessment) rounds administered since 2000. A key argument for using these test scores is the cross-country coverage. Information exist for all countries except Malta. The final sample thus reduces to the 38 countries listed in appendix table 4.

Appendix C: Sensitivity of σ estimation

Table 17: Estimates for the Construction sector

	Specification	σ	90%	α	ν	ν_K	ν_H
(1)	PF pooled neutral	0.66	(0.86-0.54)		0.00		
(2)	PF pooled directed	0.66	(0.90-0.53)			0.00	0.00
(3)	PF FE neutral	1.03	(1.72-0.74)		0.00		
(4)	PF FE directed	0.88	(1.93-0.57)			-0.05	0.02
(5)	PF FE directed $\hat{\alpha}$	0.53	(1.26-0.34)	0.10		0.00	0.00
(6)	NLSUR pooled neutral	0.52	(0.57-0.48)		0.00		
(7)	NLSUR pooled directed	0.51	(0.55-0.47)			0.01	-0.03
(8)	NLSUR FE neutral	0.45	(0.52-0.40)		0.00		
(9)	NLSUR FE directed	0.45	(0.53-0.40)			0.01	0.00
(10)	NLSUR FE directed $\hat{\alpha}$	0.50	(0.59-0.43)	0.46		-0.02	0.00

Note: Estimates of sector elasticity of substitution between physical capital and human capital, σ, based on different imposed values of η. α represents the capital share and is set to the geometric sample average (0.34) if not estimated. ν, ν_K, and ν_H represent neutral, capital-, and labor-directed technical change, respectively. Specifications: *PF:* Normalized production function only. *NLSUR:* Two-step FGNLSUR on a normalized supply side system. *pooled:* All observations pooled. *FE:* country-fixed effects included. N = 494. Estimates rounded to two digits.

Table 18: Estimates for Distribution Services

	Specification	σ	90%	α	ν	ν_K	ν_H
(1)	PF pooled neutral	0.74	(1.04-0.58)		0.02		
(2)	PF pooled directed	0.78	(1.05-0.61)			-0.06	0.11
(3)	PF FE neutral	0.64	(0.99-0.47)		0.02		
(4)	PF FE directed	0.61	(1.04-0.43)			0.01	0.02
(5)	PF FE directed $\hat{\alpha}$	0.59	(1.38-0.38)	0.41		0.01	0.02
(6)	NLSUR pooled neutral	0.59	(0.64-0.55)		0.02		
(7)	NLSUR pooled directed	0.55	(0.59-0.52)			0.01	0.02
(8)	NLSUR FE neutral	0.53	(0.58-0.49)		0.03		
(9)	NLSUR FE directed	0.53	(0.58-0.49)			0.03	0.03
(10)	NLSUR FE directed $\hat{\alpha}$	0.61	(0.66-0.57)	0.57		0.00	0.04

Note: Estimates of sector elasticities of substitution between physical capital and human capital, σ, based on different imposed values of η. α represents the capital share and is set to the geometric sample average (0.43) if not estimated. ν, ν_K, and ν_H represent neutral, capital-, and labor-directed technical change, respectively. Specifications: *PF:* Normalized production function only. *NLSUR:* Two-step FGNLSUR on a normalized supply side system. *pooled:* All observations pooled. *FE:* country-fixed effects included. N = 494. Estimates rounded to two digits.

Table 19: Estimates for Finance and Business Services

	Specification	σ	90%	α	ν	ν_K	ν_H
(1)	PF pooled neutral	0.42	(0.82-0.28)		0.00		
(2)	PF pooled directed	0.42	(0.86-0.28)			-0.01	0.00
(3)	PF FE neutral	1.71	(-9.54-0.79)		0.00		
(4)	PF FE directed	0.94	(1.55-0.67)			0.13	-0.11
(5)	PF FE directed $\hat{\alpha}$	0.95	(1.47-0.70)	0.54		0.10	-0.13
(6)	NLSUR pooled neutral	0.64	(0.72-0.58)		0.00		
(7)	NLSUR pooled directed	0.57	(0.63-0.51)			0.01	-0.02
(8)	NLSUR FE neutral	0.55	(0.63-0.48)		0.00		
(9)	NLSUR FE directed	0.57	(0.66-0.50)			0.04	-0.02
(10)	NLSUR FE directed $\hat{\alpha}$	0.65	(0.77-0.57)	0.58		0.00	-0.01

Note: Estimates of sector elasticity of substitution between physical capital and human capital, σ, based on different imposed values of η. α represents the capital share and is set to the geometric sample average (0.45) if not estimated. ν, ν_K, and ν_H represent neutral, capital-, and labor-directed technical change, respectively. Specifications: *PF:* Normalized production function only. *NLSUR:* Two-step FGNLSUR on a normalized supply side system. *pooled:* All observations pooled. *FE:* country-fixed effects included. N = 494. Estimates rounded to two digits.

Table 20: Estimates for Manufacturing

	Specification	σ	90%	α	ν	ν_K	ν_H
(1)	PF pooled neutral	0.66	(3.58-0.37)		0.02		
(2)	PF pooled directed	0.64	(1.48-0.41)			-0.09	0.13
(3)	PF FE neutral	0.59	(0.82-0.46)		0.02		
(4)	PF FE directed	0.47	(0.88-0.32)			0.01	0.03
(5)	PF FE directed $\hat{\alpha}$	0.49	(1.06-0.32)	0.52		0.01	0.03
(6)	NLSUR pooled neutral	0.68	(0.76-0.61)		0.03		
(7)	NLSUR pooled directed	0.50	(0.52-0.47)			0.00	0.00
(8)	NLSUR FE neutral	0.52	(0.56-0.49)		0.04		
(9)	NLSUR FE directed	0.52	(0.55-0.48)			0.03	0.04
(10)	NLSUR FE directed $\hat{\alpha}$	0.64	(0.69-0.60)	0.61		-0.01	0.06

Note: Estimates of sector elasticity of substitution between physical capital and human capital, σ, based on different imposed values of η. α represents the capital share and is set to the geometric sample average (0.44) if not estimated. ν, ν_K, and ν_H represent neutral, capital-, and labor-directed technical change, respectively. Specifications: *PF:* Normalized production function only. *NLSUR:* Two-step FGNLSUR on a normalized supply side system. *pooled:* All observations pooled. *FE:* country-fixed effects included. N = 494. Estimates rounded to two digits.

Table 21: Estimates for Personal Services

	Specification	σ	90%	α	ν	ν_K	ν_H
(1)	PF pooled neutral	0.38	(0.69-0.26)		-0.02		
(2)	PF pooled directed	0.37	(0.79-0.24)			-0.01	-0.02
(3)	PF FE neutral	0.79	(0.95-0.68)		-0.01		
(4)	PF FE directed	0.78	(1.06-0.62)			-0.01	-0.01
(5)	PF FE directed $\hat{\alpha}$	0.73	(1.05-0.56)	0.24		0.00	-0.01
(6)	NLSUR pooled neutral	0.53	(0.55-0.51)		-0.01		
(7)	NLSUR pooled directed	0.46	(0.48-0.44)			-0.01	-0.04
(8)	NLSUR FE neutral	0.46	(0.50-0.42)		-0.01		
(9)	NLSUR FE directed	0.46	(0.51-0.43)			0.00	-0.01
(10)	NLSUR FE directed $\hat{\alpha}$	0.56	(0.61-0.52)	0.52		-0.03	-0.01

Note: Estimates of sector elasticity of substitution between physical capital and human capital, σ, based on different imposed values of η. α represents the capital share and is set to the geometric sample average (0.32) if not estimated. ν, ν_K, and ν_H represent neutral, capital-, and labor-directed technical change, respectively. Specifications: *PF:* Normalized production function only. *NLSUR:* Two-step FGNLSUR on a normalized supply side system. *pooled:* All observations pooled. *FE:* country-fixed effects included. N = 494. Estimates rounded to two digits.

Appendix D: Development Accounting with CES and Harrod-neutral technological change

This paper uses a CES specification in the form

$$Y_{ci} = [\alpha_{ci} \left(A_{ci}^K K_{ci}\right)^{\rho_i} + (1 - \alpha_{ci}) \left(A_{ci}^H H_{ci}\right)^{\rho_i}]^{\frac{1}{\rho_i}}$$

where A_{ci}^K and A_{ci}^H are Solow– and Harrod-neutral technology terms, respectively. Clearly, there are alternative ways to consider non-neutral technology. For instance, Aiyar and Dalgaard (2009) and Mello and de Souza Rodrigues (2017) also consider a production function with Harrod-neutral technology in the form

$$Y_{ci} = [\alpha_{ci} \left(K_{ci}\right)^{\rho_i} + (1 - \alpha_{ci}) \left(A_{ci}^H H_{ci}\right)^{\rho_i}]^{\frac{1}{\rho_i}}$$

Interestingly, both studies find that the conclusions coming from the two production functions are contradictory. To be more specific, using the approach proposed by Klenow and Rodriguez-Clare (1997) and data from Caselli (2005), Aiyar and Dalgaard (2009) find that differences in factor endowments can explain 24% of the income variation across countries in a standard Cobb-Douglas specification with Harrod-neutral technology. If they instead impose a $\sigma = 1.5$, factor endowments can account for 32%. For $\sigma = 0.8$, they estimate a value of 21%. Using a more recent version of the Penn World Tables (PWT 9.0), Mello and de Souza Rodrigues (2017) estimate that factor endowments explain about 20% in a Cobb-Douglas specification, about 35% if $\sigma = 1.5$, and only 15% if $\sigma = 0.8$ in the early 2000s. In contrast, in a framework with both Solow– and Harrod-neutral technology terms, both studies find that a lower elasticity of substitution substantially increases the explanatory power of factor endowments.

We have already discussed one potential explanation for this deviation. Namely, the sensitivity of the development accounting results based on the specific technology combination imposed on all countries. Both Aiyar and Dalgaard (2009) and Mello and de Souza Rodrigues (2017) assign the U.S. technology parameters to all countries.

We now want to briefly point to a second issue. For this, it is convenient to consider a production function with Hicks-neutral technical change, physical capital and labor

$$Y_c = A_c [\alpha_{ci} \left(K_c\right)^{\rho} + (1 - \alpha_c) \left(L_c\right)^{\rho}]^{\frac{1}{\rho}}$$

in its normalized form

$$Y_c = Y_0 A_c [\alpha_0 \left(\frac{K_c}{K_0}\right)^{\rho} + (1 - \alpha_0) \left(\frac{L_c}{L_0}\right)^{\rho}]^{\frac{1}{\rho}}$$

Essentially, normalization reshapes the surface of the production function without shifting it so that CES functions characterized by the same normalization points and distribution parameters but different elasticities of substitutions are tangents. Importantly, the point of tangency is not random, but the chosen normalization point. The normalization point therefore influences how the production surface is reshaped by changing the elasticity of substitution.

Now note that all CES functions are at least implicitly normalized at $K_0 = L_0 = Y_0 = 1$. As a result of this normalization, the effect of changes in the elasticity of substitution on the production surface is larger for countries with greater physical capital per worker, k. Now further recall, that we have estimated that $\rho < 0$, implying $0 < \sigma < 1$. This implies that the role of A for explaining output per worker,y, increases with k.

This has a straightforward implication for the *success* ratio. If there is a strong positive correlation between k and y (which there is in the data), then the upward bias on A increases with y. As a result, gaps in A are larger, and thus, barriers to technology explain a larger fraction of the variation in y. A similar problem applies to a framework with Harrod-neutral technology. In contrast, development accounting results based on Solow– and Harrod-neutral technology terms are robust to different normalization points.