Human Capital and Development Accounting Revisited*

Hannes Malmberg†

Click Here for Latest Version

July 10, 2017

Abstract

Development accounting exercises generally assume that skilled and unskilled labor services are perfect substitutes. However, it is known that if labor services are imperfectly substitutable, this assumption might lead to an overestimation of uniform efficiency differences, and an underestimation of skilled labor efficiency differences. To quantify the importance of this mechanism, one needs to estimate the efficiency-adjusted relative price of skilled and unskilled labor services across countries. In this paper, I develop a method to estimate this relative price using international trade data. My method exploits the negative relationship between relative prices of skilled labor services and relative export values in skill-intensive industries. The trade data analysis suggests that the relative price of skilled labor services is low in rich countries. When I integrate these results into a development accounting exercise, I find that skilled labor efficiency differences are more important than uniform efficiency differences in explaining income differences across countries. The share of income differences explained by uniform efficiency differences falls from 79% to 26%. Under an assumption of neutral technology differences, like in traditional development accounting, the skilled labor efficiency differences reflect human capital quality differences, and these differences can explain a majority of income differences across countries. If the assumption of skill-neutral technology differences is relaxed, then an alternative explanation is that there are large skill-biased technology differences between rich and poor countries.

*I am grateful to Timo Boppart, Axel Gottfries, John Hassler, Karl Harmenberg, Per Krusell, Erik Öberg, and Torsten Persson for extensive comments on the project. Moreover, I am grateful for helpful discussions with Ingvild Almås, Konrad Burchardi, Saman Darougheh, Niels-Jakob Harbo Hansen, Loukas Karabarbounis, David Lagakos, Bo Malmberg, Kurt Mitman, Jon de Quidt, Jósef Sigurdsson, Lena Sommestad, and David Strömberg, as well as for helpful suggestions during interviews, meetings, and seminars during my job market.

†Graduate student. Institute for International Economic Studies. Email: hannes.malmberg@iies.su.se.

1 Introduction

In growth and development economics, an influential view is that income differences across countries are primarily driven by large skill-neutral labor efficiency differences. A central piece of evidence for this view comes from the development accounting literature, which uses neo-classical production theory together with price and quantity data to decompose income differences across countries into contributions from differences in capital-output ratios, human capital stocks and uniform labor efficiency levels (TFP) (Klenow and Rodriguez-Clare, 1997; Hall and C Jones 1999). An important feature of this literature has been to aggregate labor input by converting the workforce into unskilled equivalent labor units using relative wage data, based on an assumption that labor services are perfectly substitutable. Using this labor aggregation method, the finding has been that the number of unskilled equivalent labor units varies much less across countries than income levels, and that large uniform labor efficiency differences are needed to explain income differences across countries. Furthermore, these efficiency differences have been interpreted as reflecting technology differences, rather than human capital differences, based on a view that there are limited differences in the human capital of unskilled labor.[1]

However, an alternative view is that income differences are not due to *uniform* efficiency differences, but rather due to *skill-specific* efficiency differences. This view has been proposed in Caselli and Coleman (2006), B Jones (2014a) and Caselli (2016). These papers relax the assumption of labor services being perfectly substitutable, and show that, under this relaxed assumption, traditional development accounting exercises overestimate uniform efficiency differences, and underestimate skill-specific efficiency differences. This bias in traditional development accounting arises as imperfect substitutability implies a low relative price of skilled labor services in rich countries, which means that the skilled wage premium in rich countries understates the efficiency of skilled labor.[2]

The key difference between the two views lies in their interpretation of the pattern of skilled wage premia across countries. It is known that there are small or moderate differences in skilled wage premia between rich and poor countries countries, whereas there are large differences in the relative supply of skilled workers (Caselli, 2016). However, this fact is subject to multiple interpretations as

[1]Early contributions to development accounting are Klenow and Rodriguez-Clare (1997) and Hall and C Jones (1999). There has been an ongoing debate about the robustness of development accounting. See, for example, Acemoglu and Zilibotti (2001), Erosa et al. (2010), Schoellman (2011), B Jones (2014a), B Jones (2014b), Manuelli and Seshadri (2014), and Hendricks and Schoellman (2017). There is also a large literature seeking to explain TFP differences. E.g. Parente and Prescott (1999) and Acemoglu et al. (2007) discuss the role of technology diffusion barriers in explaining TFP differences, and Restuccia and Rogerson (2008), Hsieh and Klenow (2009), and Midrigan and Xu (2014) are a few contributions to the large literature that seeks to explain TFP differences by misallocation. See Manuelli and Seshadri (2014) for a paper questioning the view that unskilled labor has similar human capital across countries.

[2]The three papers all propose that skill-specific efficiency differences are key to explaining income differences across countries. However, they differ in their interpretation of these efficiency differences. B Jones (2014a) interprets them as reflecting a high human capital of skilled workers in rich countries, whereas Caselli and Coleman (2006) and Caselli (2016) interpret them as reflecting skill-biased technological differences.

the skilled wage premium can be decomposed as a product of relative efficiencies of skilled workers and relative prices of skilled labor services:

$$\frac{w_s}{w_u} = \frac{Q_s}{Q_u}\frac{r_s}{r_u},$$

where $\frac{Q_s}{Q_u}$ denotes the relative efficiency of skilled and unskilled workers, and $\frac{r_s}{r_u}$ denotes the relative price of skilled and unskilled labor services. The role of the two factors depends on the substitutability between skilled and unskilled labor services. Traditional development accounting assumes that there is perfect substitutability between different labor services, which means that the relative price r_s/r_u is constant across countries. This implies small variations in Q_s/Q_u, and that income differences are primarily due to uniform efficiency differences.[3] Caselli and Coleman (2006), B Jones (2014a), and Caselli (2016) instead posit a relatively low elasticity of substitution by assuming that US time series and panel estimates, e.g. from Katz and Murphy (1992), are valid for cross-country comparisons. This implies that r_s/r_u falls rapidly with income, and that Q_s/Q_u is high in rich countries. Indeed, for substitution elasticities within the range found in US time series studies, there are no uniform efficiency differences, and all efficiency differences are skill specific.

It is challenging to discriminate between these two interpretations since this requires us to know the value of r_s/r_u. As r_s/r_u is the relative *efficiency-adjusted* price of skilled and unskilled labor services, it is not possible to infer it directly from skilled wage premia, and we need additional information or theoretical structure to measure its value.

In this paper, I revisit the relative importance of uniform versus skill-specific efficiency differences. I do so by bringing in new evidence from international trade data to assess how r_s/r_u varies across countries. For quantification, I develop a method for analyzing industry-level export data through the lens of a gravity model. My method exploits the negative relationship between efficiency adjusted relative prices of skilled labor services and relative export levels in skill-intensive industries.

The trade data analysis provides support for the existence of skill-specific efficiency differences. Depending on the assumed trade elasticity, rich countries have an approximately 10-50 times lower efficiency-adjusted relative prices of skilled and unskilled labor services, as compared to poor countries. Even though rich countries have lower skilled wage premia than poor countries, this cannot fully explain the low relative prices of skilled labor services. In other words, high German exports in skill intensive industries cannot be fully explained by low German skilled wage premia. Thus, the analysis suggests that skilled workers are relatively more efficient in rich countries.

[3]The perfect substitutability approach was taken in the initial contributions in the development accounting literature (Klenow and Rodriguez-Clare, 1997; Hall and Jones, 1999; Caselli, 2005). A number of recent contributions in the development accounting literature have also retained the assumption of perfectly substitutable labor services (Erosa et al., 2010; Manuelli and Seshadri, 2014; Hendricks and Schoellman, 2017), as has the recent handbook chapter by C Jones (2015).

In a second stage, I place more assumptions on the aggregate economy to integrate the trade-based estimates into a standard development accounting exercise. More formally, I assume that the estimated relative prices r_s/r_u for the traded sector are the same as in the rest of the economy, and that there exists a human capital aggregator of the form

$$h = G(Q_u u, Q_s s). \tag{1}$$

Here, u and s denote the share of unskilled and skilled workers, and Q_u and Q_s denote their respective efficiencies. G is an arbitrary constant returns to scale aggregator, and the setup allows for a nested structure where the aggregate supply of skilled services $Q_s s$ reflects an aggregator of underlying heterogeneous skilled labor services. Thus, this specification of G includes the case of perfect substitutability, the case with a CES aggregator of skilled and unskilled labor services (Caselli and Coleman, 2006; Caselli, 2016), and a nested CES structure (B Jones, 2014a). In my quantitative exercise, I estimate Q_u and Q_s, and I identify an appropriate approximation of G.

To measure the human capital aggregator G, I assume that labor markets are competitive, which implies that the relative price of skilled and unskilled labor services can be equated to the marginal rate of transformation of the human capital aggregator: $r_s/r_u \doteq G_s/G_u$. Under these assumptions, I can use my measures of r_s/r_u to estimate G. First, it is possible to use r_s/r_u to back out relative labor efficiencies Q_s/Q_u using that the skilled wage premium equals the relative efficiency of skilled and unskilled workers, times the relative price of skilled and unskilled labor services:

$$\frac{w_s}{w_u} = \frac{Q_s}{Q_u}\frac{r_s}{r_u}.$$

Furthermore, the relationship between r_s/r_u and the relative labor service supply $\frac{Q_s s}{Q_u u}$ defines the isoquants of G, which can be used to identify G.

My trade data analysis suggests that there is a strong negative relationship between country income levels and the relative price of skilled labor services. Given that there is also a strong positive relationship between country income levels and relative supplies of skilled labor, this suggests that skilled and unskilled labor services are imperfectly substitutable. Furthermore, I find that the human capital aggregator G can be well approximated by a CES function, and in my baseline specification, the estimated elasticity of substitution is 1.27.

I incorporate the measurement of G into the development accounting setting of Hall and C Jones (1999). I posit an aggregate production function

$$\frac{Y}{L} = \left(\frac{K}{Y}\right)^{\frac{\alpha}{1-\alpha}} Ah,$$

where Y is output, L is the size of the workforce, K is physical capital, A is a uniform TFP-shifter, and h is a human capital aggregator of the form in equation (1).[4] When I constrain the human capital aggregator G to be additive, I find that variations in the value of G can only explain 12% of world income differences. This is in line with the role attributed to human capital in traditional development accounting. When I allow for imperfect substitutability, the share of income differences explained by differences in the value of G increases to 65%. The importance of uniform labor efficiency differences decreases correspondingly: the estimated difference in log uniform TFP differences between rich and poor countries falls by 66%.

Compared to traditional development accounting, the importance of skill-specific efficiency differences suggests a different set of interpretations of income differences across countries. The exact interpretation depends on the source of skill-specific efficiency differences.

If one retains the assumption of neutral technology differences from the traditional development accounting literature, the high efficiency of skilled workers in rich countries reflects a high human capital of skilled workers. Under this interpretation, human capital differences explain a majority of income differences across countries. The human capital interpretation is proposed in B Jones (2014a). In a complementary paper (B Jones, 2014b), Jones further explains how human capital differences can lead to large efficiency differences through an aggregation of specialized types of skilled services.

An alternative interpretation is that the high efficiency of skilled workers in rich countries reflects skill-biased technology differences, which would mean that traditional development accounting is incorrect in assuming that technology differences are neutral. This is the interpretation in Caselli and Coleman (2005) and Caselli (2016). Under this interpretation, human capital is less important than technology in explaining income differences across countries, but theories of technology differences should place a relatively larger focus on why these differences are specific to skilled occupations.

The human capital and technology interpretations are isomorphic in price and quantity data, as they both imply that skilled workers in rich countries supply more skilled labor services on average. Thus, to discriminate between the two interpretations, one needs to exploit other sources of evidence.

One promising source of evidence is migrant wage data. Wages of migrants data have been used to discriminate between human capital and technology interpretations of income differences, based on the notion that upon migration, a worker changes technology but not human capital (Hendricks, 2002; Hendricks and Schoellman, 2017). In Section 4, I analyze the possibility of using migrant wage data in my setting to discipline the sources of skilled labor efficiency differences.

[4] The equation expresses output per worker as a function of the capital-output ratio rather than the capital-labor ratio. This follows Hall and C Jones 1999 and takes into account the indirect effect of labor efficiency on capital accumulation. To separate between TFP and unskilled labor quality Q_u, my baseline analysis follows Hall and C Jones 1999 and assumes that unschooled workers are similar across countries. If Q_u is higher in rich countries, this would further reduce the differences in A across rich and poor countries.

I first note that when labor services are imperfect substitutes, it is less straightforward to interpret wage changes at migration as just reflecting technology differences. The reason is that with imperfect substitutability, different countries have different relative prices of different labor services, which means that wage changes after migration reflect a composite of technology differences, different relative prices facing workers, and occupational switching by migrants as changing relative prices implies a changing comparative advantage. A full analysis of migrant data thus requires a careful treatment of the substitutability between different types of labor services as well as of occupational choice.

Such an analysis lies beyond the scope of this paper, but I show that it is possible to provide a lower bound on the importance of human capital using summary statistics on wage changes at migration from Hendricks and Schoellman (2017). They observe pre-migration wages for a sample of migrants to the US, and find that migrants from poor countries triple their incomes upon migrating to the US. Assuming that wage changes for skilled workers moving to the US only reflects differences in skilled service prices, technologies, and capital intensities, I show how the trade data estimates can be used to calculate that at least a quarter of the skill-specific efficiency differences reflect human capital differences among skilled workers. This estimate is likely to be a lower bound of the importance of human capital, as the analysis neglects the potential for occupational switching, as well as the potential of wage increases at migration being due to complementarities with other skilled workers.

The outline of the paper is as follows. Section 2 develops the estimation strategy for the relative price of skilled labor services r_s/r_u. Section 3 presents the development accounting results. Section 4 discusses the alternative economic interpretations of my results, focusing on the interpretation of skilled labor efficiency differences as depending on human capital or skill-augmenting technology differences. Section 5 performs a large number of robustness checks on the baseline results, and Section 6 concludes the paper.

Related literature. My paper is part of the development accounting literature, going back to Klenow and Rodriguez-Clare (1997) and Hall and C Jones (1999). This literature is surveyed in Caselli (2005), Hsieh and Klenow (2010a), and C Jones (2015). There has been a number of papers revisiting the contribution of human capital in development accounting, most often in a framework featuring perfect substitutability between different types of labor services. These papers include Hendricks (2002), Erosa et al. (2010), Schoellman (2011), Manuelli and Seshadri (2014), and Hendricks and Schoellman (2017).

A few papers have analyzed development accounting with imperfectly substitutable labor services. These papers include Caselli and Coleman (2006), Caselli and Ciccone (2013), B Jones (2014a), and Caselli (2016).

Beyond development accounting, my paper builds on the gravity trade literature to estimate the relative prices of skilled services (Tinbergen, 1962; Anderson et al., 1979; Eaton and Kortum, 2002; Anderson and van Wincoop, 2003; Redding and Venables, 2004; Costinot et al., 2011; Head and Mayer, 2014). A number of papers have used trade data to obtain information about productivities, including Trefler (1993) and Levchenko and Zhang (2016). Morrow and Trefler (2017) is a more recent contribution that integrates trade into development accounting. My paper also relates to the literature that uses industry data to obtain information about economic development, which includes Rajan and Zingales (1998) and Ciccone and Papaioannou (2009). In the context of trade, papers that analyze the relationship between country variables and the industrial structure of trade include Romalis (2004), Nunn (2007), Chor (2010), Cuñat and Melitz (2012), and Manova (2013). This literature is reviewed in Nunn and Trefler (2015).

2 Estimating the relative price of skilled services

The aim of this section is to estimate how the efficiency-adjusted relative price of skilled and unskilled labor services r_s/r_u varies across countries. For this purpose, I construct a method for estimating relative factor service prices in general.

My estimation strategy is based on two premises. The first premise is that relative factor service prices influence relative unit production costs. To illustrate this, we can consider a case with two industries. Consider Table 1, which shows the factor shares for "Cut and Sew Apparel" (NAICS code 3152) and "Communications Equipment" (NAICS code 3342). Production of Communications Equipment is more skill intensive than production of Cut and Sew Apparel. If the relative price of skilled services rises, we can expect a rise in the relative unit production cost of Communications Equipment as compared to that of Cut and Sew Apparel.[5]

The second premise is that relative unit production costs affect relative export flows, which is a version of the principle of comparative advantage. For example, consider Table 2, which presents a number of US and Indonesian export values to Japan. Relative Indonesian-US exports are much higher in Cut and Sew Apparel as compared to Communications Equipment. Applying the principle of comparative advantage, this evidence suggests that Indonesia has a high relative unit production cost of Communications Equipment.

In combination, my two premises suggest that trade data contain information about relative factor service prices. For example, the trade data in Table 2 suggest that Indonesia has a high relative unit production cost of Communications Equipment. Furthermore, factor shares in Table 1 suggest that Communications Equipment production is more skill intensive than Cut and Sew Apparel production. These two facts together suggest that Indonesia has a high relative price of skilled services.

My estimation strategy formalizes and generalizes this method of obtaining information about relative factor service prices using relative export values conditional on trade destination. For this purpose, I rely on a gravity trade model. My main result is that using a version of a gravity trade model, it is possible to identify relative factor service prices using:

1. Industry factor shares
2. Bilateral industry trade data
3. The price elasticity of export flows

One particular feature of my estimation strategy is that relative unit costs are estimated from trade data. This estimation choice reflects the lack of a data set that provides detailed cross-country

[5]The cost shares are defined as shares of gross output. In Appendix A.3, I describe an alternative method where I decompose the non-tradable component of the intermediate input cost share into cost shares of other inputs using an input-output table. The final results are not affected by whether I use the basic cost shares or perform such a decomposition.

Table 1: Factor shares for Cut and Sew Apparel and Communication Equipment

	Cut and Sew Apparel	Communications Equip.
Factor services (f)	US factor shares	US factor shares
Unskilled labor	0.08	0.03
Skilled labor	0.05	0.11
Capital	0.32	0.39
Intermediate inputs	0.54	0.46
Energy	0.01	0.01
Sum	1.00	1.00

Table 2: Selected export values from Indonesia and USA to Japan (thousands of US dollars)

Origin	Destination	Industry	Export value
Indonesia	Japan	Cut and Sew Apparel	565,993
USA	Japan	Cut and Sew Apparel	197,100
Indonesia	Japan	Communications Equip.	16,503
USA	Japan	Communications Equip.	236,103

comparable industry unit cost data, which cover both rich and poor countries. The best available data set comes from the Groningen Growth and Development Center, which has done important work in constructing a data set of industry unit costs for cross-country comparisons (Inklaar and Timmer, 2008). However, their data set only covers 35 industries in 42 countries, with a limited coverage of poor countries. In contrast, trade data are recorded at a highly detailed industry level in both rich and poor countries. This makes trade data an attractive source of information for development accounting. In Section 5.3, I show that for countries where we have both unit cost data and trade data, analyses using unit cost data and trade data yield similar results.

2.1 Setup

This section describes the setup of my estimation exercise. The notation is summarized in Table 3.

There are $I = 103$ countries, and each country has $K = 84$ industries.[6] The industries correspond to NAICS four-digit manufacturing industries. I observe the value of trade flows $x_{i,j}^k$ from country i to country j in industry k. Each industry produces a good using $F = 5$ factor services. In my baseline analysis, these are services from unskilled labor, skilled labor, capital, intermediate inputs, and energy. $r_{i,f}$ denotes the price of factor service f in country i. The unit production cost

[6]The countries correspond to the countries with available data on export values, output levels, capital stocks, schooling levels, and shares of workers in skilled occupations.

Table 3: Notation

Variable	Description
i	Origin country
j	Destination country
k	Industry
f	Factor service ($f = 1$ unskilled labor services)
$x_{i,j}^k$	Export value of industry k from country i to country j
$r_{i,f}$	Factor service price of factor f in country i
$\alpha_{i,f}^k$	Cost share of factor f in industry k in country i
c_i^k	Unit cost of industry k in country i
σ	Price elasticity of trade

c_i^k of industry k in country i is a function of factor service prices. The relationship is given by

$$c_i^k = \frac{C^k(r_{i,1}, \ldots, r_{i,F})}{Z_i}.$$

This assumption implies that there is an industry cost function C^k that is common across countries. In an individual country, the unit cost function c_i^k is derived by deflating the common industry cost function C^k with a country-specific productivity term Z_i, which is common across industries. This particular setup implies that cross-country differences in relative unit costs only stem from cross-country differences in relative factor service prices. However, as the factor service prices are efficiency-adjusted, the setup is consistent with cross-country differences in factor augmenting technologies, and factor quality differences.[7]

2.2 Key equations

My estimation builds on the following two equations:

$$\begin{aligned} \log(x_{i,j}^k) &= \delta_{i,j} + \mu_j^k - (\sigma - 1)\log(c_i^k) && (2) \\ \log(c_i^k) &= \log(c_{US}^k) + z_i + \sum_{f=2}^{F} \alpha_{US,f}^k \log\left(\frac{r_{i,f}/r_{i,1}}{r_{US,f}/r_{US,1}}\right), && (3) \end{aligned}$$

where $z_i = \log\left(\frac{r_{i,1}}{r_{US,1}}\right) - \log\left(\frac{Z_i}{Z_{US}}\right)$ is the log deviation in unskilled labor service prices, adjusted for absolute productivity differences. The first equation (2) is a gravity trade equation. The log export value from country i to country j in industry k depends on three terms. The first term is a bilateral fixed effect $\delta_{i,j}$. It captures determinants of overall bilateral trade flows such as the size of

[7] In Section 5.1, I discuss regression specifications that address other potential confounders in the specification of unit costs.

the two countries, their bilateral distance, common legal origins, shared language, etc. The second term is a destination-industry fixed effect μ_j^k, which captures the demand for good k in destination j, as well as how good access country j has to industry k, given its other trading partners. The third term captures that conditional on the two fixed effects, exports depend negatively on origin unit production costs, with a price elasticity $\sigma - 1$. In Appendix A.1, I show how equation (2) can be derived from both a trade model in the style of Eaton and Kortum (2002), where trade is driven by country-variety specific productivity shocks, and from an Armington model where each country produces a unique variety of each good k.

The second equation (3) is a log-linear approximation of industry unit costs around the US cost structure, where $f = 1$ indexes unskilled labor services. I obtain the approximation in two steps. I first note that

$$\begin{aligned}
\log(C_i^k) &\approx \log(C_{US}^k) + \sum_{f=1}^{F} \frac{\partial C^k}{\partial r_f} \frac{r_{US,f}}{C^k} \log\left(\frac{r_{i,f}}{r_{US,f}}\right) \\
&= \log(C_{US}^k) + \sum_{f=1}^{F} \alpha_{US,f}^k \log\left(\frac{r_{i,f}}{r_{US,f}}\right)
\end{aligned}$$

where C^k is the common cost function of industry k, and $\alpha_{US,f}^k$ denotes the US factor share of factor f in industry k. The second line uses Shepherd's lemma applied to the cost function to conclude that $\alpha_{US,f}^k = \frac{\partial C^k}{\partial r_f} \frac{r_{US,f}}{C^k}$ when firms are price-takers.

Combining this expression with $c_i^k = \frac{C^k(r_{i,1},\ldots,r_{i,F})}{Z_i}$ gives me

$$\log(c_i^k) = \log(c_{US}^k) + \log\left(\frac{Z_i}{Z_{US}}\right) + \sum_{f=1}^{F} \alpha_{US,f}^k \log\left(\frac{r_{i,f}}{r_{US,f}}\right). \tag{4}$$

I re-arrange this equation to equation (3), as my aim is to find the *relative* price of factor services compared to unskilled labor services, $\log\left(\frac{r_{i,f}/r_{1,f}}{r_{US,f}/r_{US,1}}\right)$. This makes it useful to normalize equation (4) with the price of unskilled labor services. I use the fact that factor shares sum to 1 to express the unskilled cost share $\alpha_{US,1}^k$ in terms of the other cost shares: $\alpha_{US,1}^k = 1 - \sum_{f=2}^{F} \alpha_{US,f}^k$. Substituting this expression into (4) gives me equation (3).

Equation (3) decomposes log unit cost differences from the US into one term capturing absolute productivity differences, one term capturing differences in the cost of unskilled labor, and a linear combination of relative factor service price differences times US factor shares. Equation (3) shows that countries with a relatively high factor service price in factor f (high $\log\left(\frac{r_{i,f}/r_{i,1}}{r_{US,f}/r_{US,1}}\right)$) will have relatively high unit costs in sectors intensive in factor f (relatively high $\alpha_{US,f}^k$)).

As explained, equation (3) comes from a log linear approximation around the US cost structure. If industry production functions are Cobb-Douglas, this approximation is exact. If industry production functions are not Cobb-Douglas, there is a second-order bias. In Section 5.1, I analyze the effect of relaxing the Cobb-Douglas assumption.

2.3 Regression specification

To derive my regression specification, I combine the gravity equation (2) and the unit cost equation (3). I obtain

$$\log(x_{i,j}^k) = \tilde{\delta}_{i,j} + \tilde{\mu}_j^k - (\sigma - 1) \sum_{f=2}^{F} \alpha_{US,f}^k \log\left(\frac{r_{i,f}/r_{i,1}}{r_{US,f}/r_{US,1}}\right).$$

Here, $\tilde{\delta}_{i,j} = \delta_{i,j} - (\sigma - 1)\left(\log\left(\frac{r_{i,1}}{r_{US,1}}\right) - \log\left(\frac{Z_i}{Z_{US}}\right)\right)$ denotes a modified fixed effect that includes the trade bilateral fixed effect, the origin absolute advantage, and the origin unskilled factor service prices. The term $\tilde{\mu}_j^k = \mu_j^k - (\sigma - 1)\log(c_{US}^k)$ denotes a modified fixed effect that includes the trade destination-industry fixed effect μ_j^k and US industry unit costs.

I can use this equation to derive a regression specification. For this purpose, I note that I can measure $x_{i,j}^k$ from international trade data, that I can measure $\alpha_{US,f}^k$ from American industry data, and that I can use the trade literature to obtain estimates of σ.[8] Thus, $\log(x_{i,j}^k)$ is my left-hand variable, and $(\sigma-1)\alpha_{US,f}^k$ for $f = 2, \ldots, F$ are my explanatory variables. My aim is to estimate the relative factor service price differences $\log\left(\frac{r_{i,f}/r_{i,1}}{r_{US,f}/r_{US,1}}\right)$. This quantity varies on a country-factor basis. Therefore, I want to estimate one parameter for each factor-country combination, and I write $\beta_{i,f}$ for this set of parameters. Given the interpretation of $\beta_{i,f}$ as differences in relative factor service prices compared to those in the US, I normalize $\beta_{i,f}$ by setting $\beta_{US,f} = 0$ for all f.

I obtain the following specification:

$$\log(x_{i,j}^k) = \tilde{\delta}_{i,j} + \mu_j^k - \sum_{f=2}^{F} \left[(\sigma - 1)\alpha_{US,f}^k\right] \times \beta_{i,f} + \varepsilon_{i,j}^k, \tag{5}$$

with the normalization $\beta_{US,f} = 0$ for $f = 2, \ldots, F$. I regress log bilateral trade flows on a bilateral fixed effect, a destination-industry fixed effect, and $-(\sigma - 1)\alpha_{US,f}^k$ for $f = 2, \ldots, F$, allowing for country-factor specific parameters $\beta_{i,f}$. In total, I estimate $(5 - 1) \times 103 = 412$ parameters: one for each country-factor combination, excluding unskilled labor services. With this regression specification, $\beta_{i,f} = \log\left(\frac{r_{i,f}/r_{i,1}}{r_{US,f}/r_{US,1}}\right)$ identifies the difference between country i and the US in the log relative price of factor service f as compared to unskilled labor services. The difference to the US in the log relative price of skilled labor services is identified by $\beta_{i,skill}$.

[8] Some papers estimate σ directly from trade data (Broda et al., 2006; Soderbery, 2015), exploiting short-run variations in trade prices and quantities. As I am interested in the long-run elasticity of trade, I choose a calibration approach to select σ.

2.4 Data in trade regression

The regression equation (5) requires data on bilateral trade flows $x_{i,j}^k$, US factor shares $\alpha_{US,f}^k$, and a parameter estimate for the trade elasticity σ.

For trade flows, I use the BACI data set which is compiled by CEPII and based on COMTRADE (Gaulier and Zignago, 2010). For each country-destination pair, it reports export values at the HS 2007 six-digit industry level. I use data for 2010.

I measure factor shares by combining data from the NBER-CES Manufacturing Industry Database (Bartelsman and Gray, 1996) with data from the Occupational Employment Statistics (OES) survey. I use the NBER-CES database to obtain the cost shares of capital, labor, materials, and energy. I define the shares of labor, materials, and energy as factor outlays divided by industry gross output, and I define the capital share as 1 minus the other factor shares. To find the shares of skilled and unskilled services, I use the OES to calculate the share of payroll in each industry that goes to workers in occupations with skill levels 3 and 4 in the ISCO-08 classification. This corresponds to the major occupational groups "Managers", "Professionals", and "Technicians and Associate Professionals". I calculate the skill share as the labor share from the NBER CES times the share of payroll going to skilled workers, and the unskilled share as the labor share times the share of payroll going to unskilled workers. Note that in my regression, I include the materials and energy shares in the regression. Appendix A.3 provides a more detailed discussion of different choices of intermediate input measurement and their effects.

The regression is performed using NAICS four-digit coding, which is the coding scheme of the OES industry data. The trade data are recorded using HS6 codes and the NBER-CES data are recorded using NAICS six-digit codes. The OES occupational data are recorded according to SOC, and they are converted to ISCO-08 to calculate the share of payroll going to skilled workers.

I take my value of the trade elasticity σ from the literature. I look for an estimate of the *long-run* elasticity *between different foreign varieties in the same industry*. This choice reflects the nature of my regression. The regression is run between countries in different parts of the world-income distribution, and aims at capturing persistent cross-country differences. Furthermore, the regression explains a source country's exports conditioned on the total industry imports of a destination country. Thus, the relevant elasticity is the long-run elasticity between different foreign varieties.

I select $\sigma = 10$ as my baseline elasticity. This is a reasonably high estimate of trade elasticity and reflects a conservative choice for estimating the importance of skilled labor efficiency. A higher σ shrinks the importance of skilled labor efficiency since it reduces the estimated differences between countries: differences in relative trade flows translate into smaller unit cost differences. Even though Eaton and Kortum (2002) open up for estimates as high as $\sigma = 14$, my estimate is higher than $\sigma = 5$ found in Simonovska and Waugh (2014), $\sigma = 7.2$ found in Costinot et al. (2011), and the baseline $\sigma = 9.2$ found in Eaton and Kortum (2002).[9]

My baseline estimate $\sigma = 10$ corresponds to the higher range estimates found in Romalis (2007) when he estimates the trade effects of NAFTA. He calculates a pooled trade elasticity by investigating how differential reductions of tariffs due to NAFTA affected trade in the quadrangle USA, Canada, Mexico, and the EU. I select this high estimate to be conservative and due to the fact that the long-run effects of NAFTA studied by Romalis (2007) reflect the type of long-run, foreign-to-foreign substitution that my regression specification seeks to capture. In Section 5.1, I discuss the effects of making different assumptions about σ.

2.5 Results from trade regression

My main results are displayed in abridged form in Table 4. The table presents log relative factor service price estimates for different factors, and for six randomly selected countries in each World Bank Income group. Standard errors are calculated by clustering at the industry-country level.

The table shows that poor countries in general have higher relative factor service prices for skilled services, capital services, and intermediate input services. The pattern is especially pronounced for skilled services. There is some tendency for relative energy service prices to be higher in poor countries, but this pattern is less clear. Relative energy service prices vary more between similar countries and are less precisely estimated.

My primary interest is in the relative prices of skilled services, since these are used in my development accounting exercise. In Figure 1, I provide a graphical illustration of the relationship between estimated relative skilled service prices and log GDP per worker. There is a strong negative relationship, and poor countries have approximately 4-5 log points higher relative prices of skilled services. If I take standard errors into account, the results are consistent with a stable, almost linear, relationship between log GDP per worker and the log relative price of skilled services. There is a less clear relationship between log GDP per worker and skilled service prices for the very poorest countries, which could reflect that manufacturing exports are relatively unimportant in these countries. In Section 5.3, I analyze the effect of excluding the poorest countries from the analysis, and I show that this further decreases the importance of uniform efficiency differences.

Even though I do not use the other factor service price estimates in my development accounting exercise, they can be used to evaluate the estimation method. Appendix A.2 discusses the results for other factors in greater detail.

[9]Note that the trade elasticity θ in Eaton and Kortum-style models represents the elasticities of export value with respect to price changes, whereas σ represents the elasticity of quantity with respect to price changes. Hence, $\sigma = \theta + 1$ when we convert between the two types of parameters.

Table 4: Regression estimates of log relative factor service price parameters (US = 0)

	Factor services			
	Skilled labor	Capital	Intermediate inputs	Energy
Low income				
Gambia	5.64 (1.01)	2.53 (0.68)	2.56 (0.57)	−1.17 (1.01)
Liberia	4.56 (1.09)	2.73 (0.77)	2.28 (0.64)	3.03 (1.43)
Nepal	5.89 (1.15)	2.83 (0.77)	2.85 (0.74)	5.35 (1.78)
Rwanda	4.54 (1.31)	1.40 (0.75)	1.55 (0.72)	3.04 (1.78)
Tanzania	3.72 (1.03)	1.45 (0.69)	1.54 (0.55)	0.21 (1.25)
Uganda	3.09 (0.96)	0.82 (0.64)	0.93 (0.52)	1.44 (1.32)
Lower middle income				
Indonesia	3.78 (0.98)	1.41 (0.64)	1.65 (0.57)	0.47 (1.20)
Pakistan	4.92 (1.08)	2.14 (0.76)	2.35 (0.68)	2.12 (1.61)
Philippines	1.52 (1.06)	0.57 (0.73)	1.02 (0.58)	1.91 (1.20)
Tunisia	2.62 (1.03)	1.61 (0.66)	1.54 (0.55)	0.81 (1.29)
Ukraine	2.45 (0.92)	0.92 (0.63)	0.96 (0.52)	−2.30 (1.49)
Vietnam	3.60 (1.21)	2.15 (0.78)	2.39 (0.67)	3.10 (1.35)
Upper middle income				
Colombia	3.74 (0.96)	1.01 (0.59)	1.37 (0.50)	−0.87 (1.11)
Dominican Republic	3.27 (1.17)	0.65 (0.73)	1.40 (0.64)	0.75 (1.38)
Paraguay	5.67 (1.18)	1.21 (0.71)	1.27 (0.67)	1.59 (1.82)
Russia	1.12 (0.95)	0.001 (0.65)	−0.10 (0.55)	−4.57 (1.19)
South Africa	1.67 (0.90)	0.46 (0.58)	0.43 (0.47)	−1.61 (1.08)
Turkey	3.59 (0.97)	1.95 (0.60)	2.09 (0.49)	0.40 (1.18)
High income				
Chile	4.13 (1.09)	0.54 (0.65)	0.65 (0.56)	−1.20 (1.46)
Ireland	−0.10 (0.99)	−1.05 (0.68)	−0.53 (0.61)	0.21 (1.66)
Netherlands	0.59 (0.88)	−0.45 (0.56)	−0.17 (0.45)	−0.24 (1.00)
New Zealand	1.54 (0.91)	0.62 (0.62)	0.32 (0.58)	1.15 (1.19)
Taiwan	−0.10 (1.07)	1.37 (0.67)	1.27 (0.58)	0.58 (1.31)
United States	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Observations	453,147			
R^2	0.69			

Note: Standard errors are clustered on origin-industry level

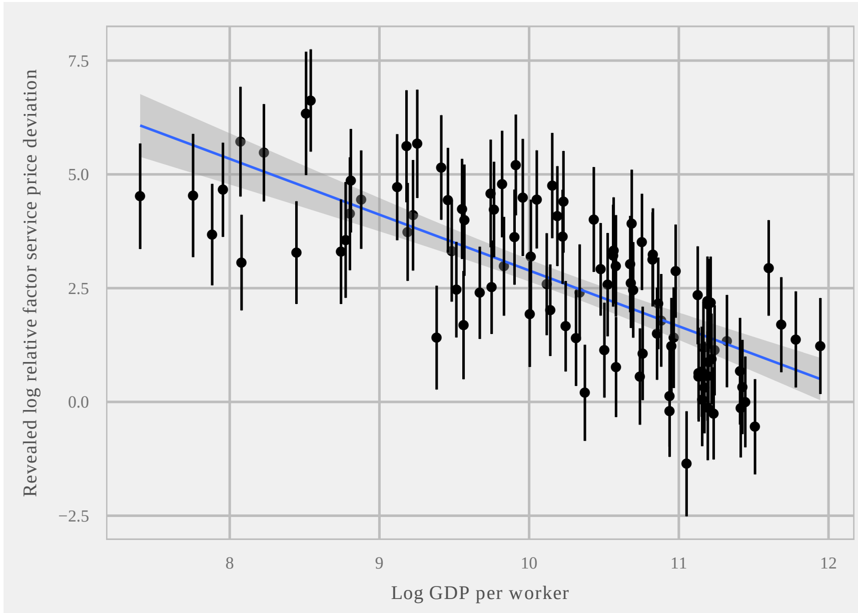


Figure 1: Log GDP per worker and log $\left(\frac{r_{i,skill}/r_{i,unskill}}{r_{US,skill}/r_{US,unskill}}\right)$

3 Development accounting

In this section, I want to use the estimates from Section 2 to perform a development accounting exercise. The aim is to decompose the variance in GDP per worker into contributions from differences in capital-output ratios, uniform labor productivity shifters and differences in human capital aggregators.

3.1 Aggregate production function

Performing development accounting requires more theoretical structure on the aggregate economy. In Section 2, the key assumption was that trade flows followed a gravity relationship. This assumption is consistent with a range of models for the aggregate economy. In contrast, for development accounting, we need an aggregate production function that summarizes both substitution possibilities within and between industries and substitution possibilities between domestic and foreign production.

It can be shown that standard trade models admit a constant returns to scale aggregate production function under relatively mild assumptions (see Appendix B.2), but there is no general result on the functional form of such an aggregate production function. In general, the aggregation of capital, skilled labor, and unskilled labor depends on trade elasticities, the input-output structure, the relative factor shares of traded and non-traded goods, and how traded and non-traded goods are aggregated. Thus, to perform development accounting, one needs to make a functional form assumption.

I follow the development accounting literature by making the assumption that the aggregate production function can be well approximated by a Cobb-Douglas aggregator of labor and capital. Moreover, I assume that the human capital aggregator is an arbitrary constant returns to scale function of the number and efficiencies of skilled and unskilled workers. This assumption allows me to focus on how labor input aggregation changes the development accounting exercise. The functional form choice is further discussed in Appendix B.3.

Thus, I posit an aggregate production function:

$$Y = K^{\alpha}(ALh)^{1-\alpha}, \tag{6}$$

where Y is total output, K is the physical capital stock, A is a labor-augmenting technology term, L is the size of the labor force, and h denotes the human capital aggregator. I allow for a flexible specification of h,

$$h = G(Q_u u, Q_s s),$$

where G is a constant returns to scale aggregator, u and s are the shares of unskilled and skilled workers, and Q_u and Q_s are the amount of unskilled/skilled services delivered by each unskilled/skilled worker. I will refer to Q_u and Q_s efficiencies of unskilled and skilled labor.

The human capital aggregator term h has two potential interpretations. One interpretation of the aggregator is that there are two homogenous skill types, with the respective efficiencies Q_u and Q_s. A second interpretation is that there are two aggregators $H_u = Q_u u$ and $H_s = Q_s s$, which combine heterogeneous types of services into an aggregate flow of unskilled and skilled services. With this interpretation, Q_u and Q_s represent the average flow of unskilled/skilled labor services per unit of unskilled/skilled labor, and w_s and w_u are the average wages of skilled and unskilled workers.

The interpretation with two types of labor services is easier to discuss, whereas the aggregator interpretation is more realistic. I will derive my results in the language of the interpretation with two labor types. I will refer to u and s as the share of unskilled and skilled workers, and to Q_u and Q_s as the (average) efficiencies of unskilled and skilled labor. When I analyze economic mechanisms, I will leverage the mathematical equivalence to interpret my results in light of the aggregator interpretation.

3.2 Estimating terms of aggregate production function

To perform development accounting, we need to measure Y, L, α and h.

Data on real output Y, labor force size L, and physical capital stock K are from the Penn World Table Version 8.1. I use data from 2010, and I set the capital share α to 1/3.

To measure $h = G(Q_u u, Q_s s)$, I use data from ILO to measure the share of skilled workers s. I define the share of skilled workers as the share of workers having an occupation requiring skill level 3 or 4. According to ILO, occupations require skill level 3 or 4 when they "typically involve the performance of [...] tasks that require an extensive body of [...] knowledge in a specialized field". In the International Standard Classification of Occupations 2008 (ISCO-08), these are "Managers", "Professionals", and "Technicians and Associate Professionals". Figure 2 shows the relationship between the share of skilled workers and log GDP per worker. There is a strong positive relationship, and a linear regression of the skill share on log GDP per worker has an R^2-value of 0.75. My skill definition differs from the literature in being occupation-based instead of schooling-based. I discuss this choice in Appendix C.1.

I calibrate the quality of unskilled labor Q_u using data on schooling levels and Mincerian returns. I define

$$Q_u = e^{\phi(S_u)}, \tag{7}$$

where S_u is the average schooling years of unskilled workers, and ϕ is a Mincerian return function capturing the relationship between schooling and wages. I measure S_u using the Barro-Lee schooling data for 2010. I assume that there is perfect positive sorting between years of schooling and working in a skilled profession, which means that unskilled workers correspond to the $1 - s$ share of the workforce with the least schooling. I assume that S_u is the average number of school years in this group.[10] I take the Mincerian return function $\phi(S)$ from Caselli (2005) and define it as a piecewise linear function with slope 0.13 for $S < 4$, slope 0.1 for $S \in [4, 8)$, and slope 0.08 for $S \geq 8$. This specification was introduced in the literature as a reduced form way of capturing that poor countries have higher Mincerian returns.

To measure the relative efficiency of skilled workers Q_s/Q_u, I assume that labor markets are competitive and that the relative price of skilled labor services r_s/r_u is valid across the economy. This means that the relative wage of skilled and unskilled workers is

$$\frac{w_s}{w_u} = \frac{Q_s}{Q_u}\frac{r_s}{r_u},$$

where

$$\frac{r_s}{r_u} = \frac{G_s}{G_u}.$$

I measure the relative efficiency of skilled and unskilled labor using the equation

$$\frac{w_s}{w_u} = \frac{Q_s}{Q_u}\frac{r_s}{r_u} \Longleftrightarrow \frac{Q_s}{Q_u} = \frac{w_s/w_u}{r_s/r_u}. \tag{8}$$

The skilled wage premium w_s/w_u is observable, and the relative price of skilled services $\frac{r_s}{r_u}$ was estimated in Section 2.[11] This equation states that the skill premium equals the relative *amount*

[10] See Appendix C.2 for details on how I calculate the average schooling of unskilled labor.

[11] In Section 2, I estimated $\frac{r_s/r_u}{r_{US,s}/r_{US,u}}$. To find r_s/r_u, I need $r_{US,s}/r_{US,u}$. I find this by normalizing US skilled

of services provided by skilled and unskilled workers, times the relative *price* of those services. Rearranging the equation shows that there will be a high estimate of relative skilled labor efficiency if either a) the skill premium is high given the price of skilled services, since this reflects a large amount of services being delivered, or b) if observed skilled service prices are low given the skill premium, since this reflects a high efficiency of skilled labor, thus bringing down the efficiency adjusted price.

I use ILO data to measure the skilled wage premium w_s/w_u. ILO summarizes wage data from multiple sources, and I restrict attention to countries where data are available from administrative records, a labor-focused establishment survey, and/or a labor force survey. I use the measure of mean nominal monthly earnings of employees. I combine data on wages and employment across occupations, and I calculate the relative average wage between workers with skill levels 3 or 4 and workers with skill levels 1 or 2. Figure 3 shows the relationship between log skilled wage premia and log GDP per worker. Apart from two outliers (Vietnam and Qatar), there is a strong negative relationship. The ILO data only cover a limited set of countries, and there are large variations between countries with similar levels of log GDP per worker. In my development accounting exercise, I want to use a large set of countries, and I am interested in systematic differences between rich and poor countries. Thus, to assign values of the skilled wage premium, I regress the log skilled premium on log GDP per worker (excluding outliers). I assign each country a skilled premium using the fitted value of this regression. This allows me to extend the country coverage beyond the limited set of countries covered in the ILO data, while capturing the systematic changes of the skilled wage premium across the GDP per worker distribution. In Section 5.3, I consider how changes in the measurement of the skilled wage premium change my results.

With estimates of r_s/r_u, Q_s/Q_u, and s/u, it is possible to estimate the functional form and parameters of the human capital aggregator G. As G has constant returns to scale, it is characterized up to a constant by the relationship between the marginal rate of transformation f_s/f_u and the relative effective labor supplies $\frac{Q_s s}{Q_u u}$. In particular, a linear relationship between $\log\left(\frac{f_s}{f_u}\right)$ and $\log\left(\frac{Q_s s}{Q_u u}\right)$ suggests that G has a constant elasticity of substitution.

Using the estimates of r_s/r_u from Section 2, we can plot the relationship between the (log) marginal rate of transformation and (log) relative effective labor supplies. However, we need to be cautious in interpreting this relationship when relative qualities Q_s/Q_u are derived using equation (8). The reason is that relative supplies are calculated by dividing skilled wage premia by r_s/r_u. This means that if there are measurement errors in r_s/r_u, this could cause a bias of the relationship between $\log\left(\frac{r_s}{r_u}\right)$ and $\log\left(\frac{Q_s s}{Q_u u}\right)$ to be negatively linear with slope -1 due to division bias. One way

labor efficiency to $Q_{US,s} = 1$. This implies:

$$\frac{r_{US,s}}{r_{US,u}} = \left(\frac{1}{Q_{US,u}}\right)^{-1} \frac{w_{US,s}}{w_{US,u}}.$$

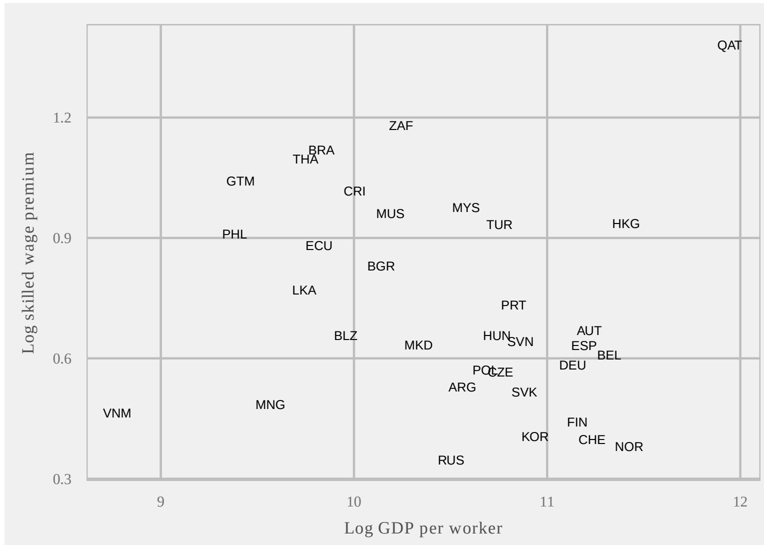


Figure 2: Log skilled wage premia versus log GDP per worker

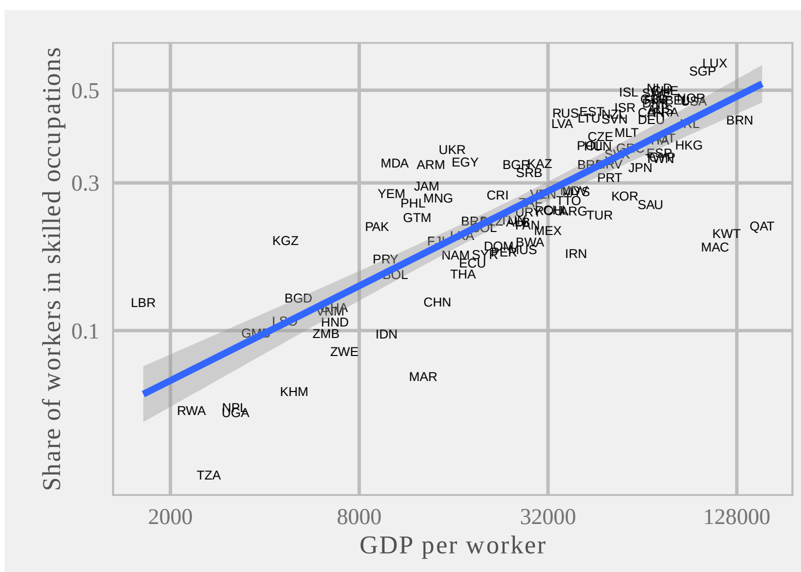


Figure 3: Log relative share of workers in skill level 3+4 vs log GDP per worker

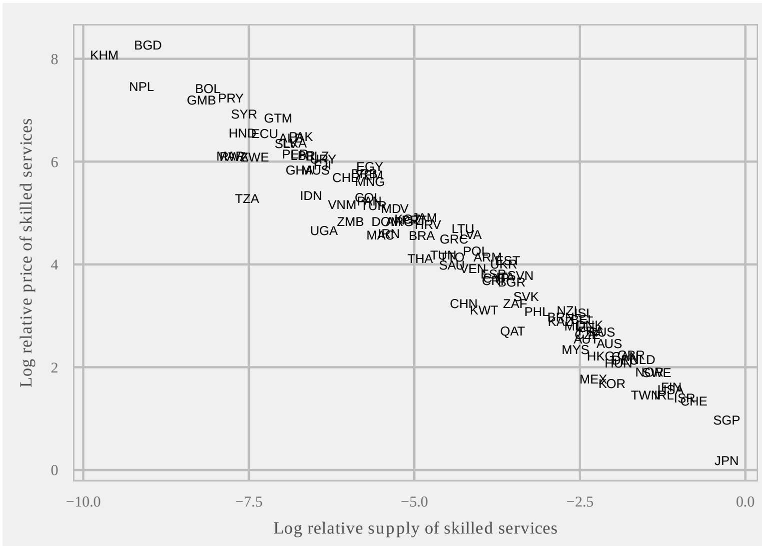


Figure 4: Log relative price of skilled services vs log relative effective skilled labor supply

of addressing this concern is to instrument log relative factor service supplies $\log\left(\frac{Q_s s}{Q_u u}\right)$ with log GDP per capita. Figure 5 shows the result both with and without instrumentation. The left-hand panel shows $\log\left(\frac{r_s}{r_u}\right)$ plotted against $\log\left(\frac{Q_s s}{Q_u u}\right)$. The right-hand panel replaces $\log\left(\frac{Q_s s}{Q_u u}\right)$ with the fitted values from a first-stage regression of $\log\left(\frac{Q_s s}{Q_u u}\right)$ on $\log(y)$ and $\log^2(y)$. Both plots suggest an approximately linear relationship between $\log\left(\frac{r_s}{r_u}\right)$ and $\log\left(\frac{Q_s s}{Q_u u}\right)$. Thus, I posit that human capital is aggregated using a constant elasticity of substitution aggregator[12]

$$G(Q_u u, Q_s s) = \left((Q_u u)^{\frac{\eta-1}{\eta}} + a_S (Q_s s)^{\frac{\eta-1}{\eta}}\right)^{\frac{\eta}{\eta-1}}.$$

To obtain estimates of the parameters a_s and η, I note that

$$\frac{w_s}{w_u} = \frac{a_S Q_s^{1-1/\eta}}{Q_u^{1-1/\eta}} \left(\frac{s}{u}\right)^{-1/\eta} \Leftrightarrow \log\left(\frac{r_s}{r_u}\right) = \log(a_s) - \frac{1}{\eta} \log\left(\frac{Q_s s}{Q_u u}\right). \tag{9}$$

I recover $\log(a_s)$ and $-1/\eta$ as the intercept and slope from a cross-country regression of log relative service prices $\log\left(\frac{r_s}{r_u}\right)$, on log relative service supplies, $\log\left(\frac{Q_s s}{Q_u u}\right)$. This specification is a close cross-country analogue of the regression specification introduced in Katz and Murphy (1992). I estimate a skill share $a_s = 2.06$, and an elasticity of substitution $\eta = 1.27$.[13]

[12] As previously noted, G is only defined up to a multiplicative constant. This means that I cannot separate the levels of A and h, but it is still possible to estimate the relative sizes of A and h across countries.

[13] The difference between my estimation and Katz and Murphy is that I use the trade data to obtain an independent estimate of the labor-augmenting terms Q_s/Q_u, whereas Katz and Murphy (1992) identify η by assuming that there is a log-linear time trend in $\frac{Q_s}{Q_u}$ and they estimate the elasticity by deviations around this trend. I also use an occupation-based definition of skill rather than an education-based definition of skill. To test the sensitivity of the

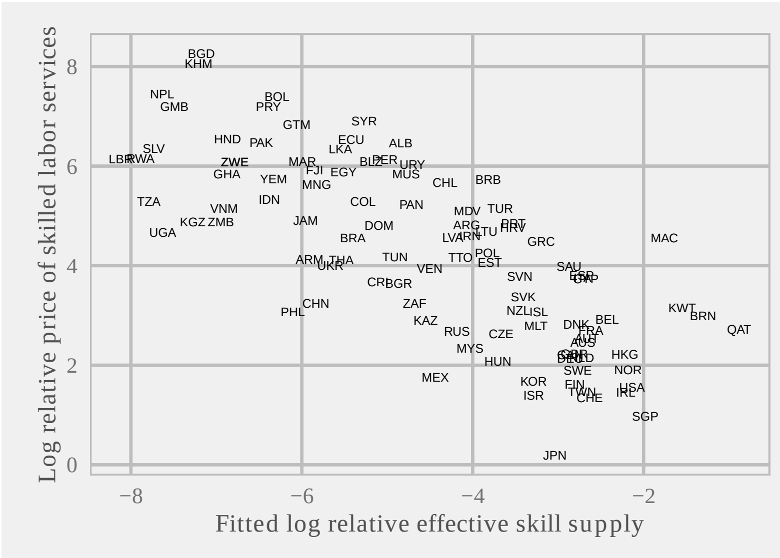


Figure 5: Log relative price of skilled services vs fitted log relative effective skilled labor supply

3.3 Results

In this section, I perform development accounting. My main outcome variables are the shares of income differences across countries that are accounted for by differences in physical capital, the human capital aggregator G, and uniform TFP differences. To evaluate how my human capital measurement method affects development accounting, I compare my results to those obtained when the human capital aggregator is additive in line with traditional development accounting methods.

To decompose income differences into contributions from factors and technology, I re-arrange the aggregate production function (6) into

$$y \doteq \frac{Y}{L} = \left(\frac{K}{Y}\right)^{\frac{\alpha}{1-\alpha}} Ah.$$

With this re-arrangement, aggregate output is expressed as a function of the capital-output ratio. This approach follows Hall and Jones (1999) and Hsieh and Klenow (2010b), and takes into account the steady-state effects of the human capital aggregator and technology differences on capital accumulation.

The aggregate production function admits a linear decomposition of log output per worker:

$$\log(y) \equiv \log\left(\frac{Y}{L}\right) = \frac{\alpha}{1-\alpha}\log\left(\frac{K}{Y}\right) + \log(h) + \log(A).$$

estimates to division bias, I have also analyzed the relationship between relative skilled and unskilled factor shares and the relative price of skilled and unskilled services. As the relative factor shares can be measured independently of r_s/r_u, this specification does not feature any division bias. I similarly find an approximate linear relationship, and similar results for the share of income differences explained by different values of the human capital aggregator G.

Using this decomposition, I define the shares of income differences attributable to different factors:

$$\begin{aligned}
\rho^K &= \frac{Cov\left(\frac{\alpha}{1-\alpha}\log\left(\frac{K}{Y}\right), \log(y)\right)}{Var(\log(y))} \\
\rho^h &= \frac{Cov\left(\log(h), \log(y)\right)}{Var(\log(y_i))} \\
\rho^A &= 1 - \rho^K - \rho^h.
\end{aligned}$$

In addition to share parameters, I define a summary measure of TFP-differences between rich and poor countries. To define this measure, I regress log TFP on log GDP per worker which gives me predicted log TFP as a function of log GDP per worker. My definition of the rich-poor log TFP difference is the change in this predicted value between the 10^{th} and the 90^{th} percentile of the GDP per worker distribution. I write $\Delta\log(A)$ for this difference.

I also calculate the share parameters and the TFP differences using an alternative measure of the human capital aggregator h_{trad}, which is constructed in line with traditional development accounting methods. It is measured by converting skilled workers to unskilled equivalents using the skilled wage premium.[14] I define h_{trad} as

$$h_{trad} = Q_u\left(u + s\frac{w_s}{w_u}\right), \tag{10}$$

where unskilled labor quality Q_u is defined in equation (7).

To compare my measure h_{new} with the traditional development accounting measure h_{trad}, I compare how the share of world income differences explained by the human capital aggregator – ρ^h – changes when I change the human capital aggregator measure from h_{trad} to h_{new}. Furthermore, I estimate the reduction in log TFP differences between rich and poor countries when I change the human capital aggregator measure from h_{trad} to h_{new}. To measure this reduction, I define the share of TFP differences explained as

$$TFP_{share} = 1 - \frac{\Delta\log(A_{new})}{\Delta\log(A_{trad})}.$$

To interpret this measure, recall that $\Delta\log(A)$ refers to the difference in log TFP between rich and poor countries. If there are no remaining TFP differences between rich and poor countries with my method of aggregating human capital, $TFP_{share} = 1$. If the TFP differences between rich and

[14] My calculation method is analogous to traditional development accounting as it calculates human capital using unskilled equivalents estimated using relative wages. The standard references in development accounting, Hall and C Jones (1999) and Caselli (2005), use a slightly different implementation as they use years of schooling as their skill measure instead of occupation, and they use Mincerian returns instead of occupation-based skilled wage premia to calculate wage differences. They define human capital as $h_i = \exp(\phi(S_i))$ where ϕ is a Mincerian return function and S_i is the average years of schooling in country i. In my setting, their method yields very similar results to using equation (10).

poor countries are the same with my method of measuring the human capital aggregator as with the traditional development accounting method, $TFP_{share} = 0$.

Table 5 presents the baseline results of my development accounting exercise. Capital-output variations explain 8% of world income differences. This share does not depend on the method of aggregating human capital. The traditional development accounting method attributes 12% of income differences across countries to the human capital aggregator, and 79% to TFP.[15] My method attributes 65% of income differences across countries to the human capital aggregator, and only 26% to TFP. Estimated log TFP differences between rich and poor countries shrink by 67% when I change the human capital aggregation method.

Table 5: Contribution of factors and TFP to income differences: baseline parametrization

	Baseline
Capital	0.08
Human capital – trad.	0.12
Human capital – new	0.65
TFP – trad.	0.79
TFP – new	0.26
Log TFP diff. – trad.	2.54
Log TFP diff. – new	0.85
TFP-diff. reduction	67%
Elasticity of subst. η	1.27

3.4 Intuition from country example: Tanzania

To make the development accounting results more concrete, I focus on what they mean for one poor country: Tanzania. In 2010, Tanzania had a GDP per worker of \$2650, which made it the 17^{th} poorest country among the 165 countries in the Penn World Table. I ask the following question: how do different human capital measurement methods predict that Tanzanian GDP per worker would change if the skill levels of the Tanzanian workforce were increased to the levels of the US workforce, keeping the Tanzanian capital-output ratio and TFP constant?

I answer this question using both the traditional development accounting method of aggregating microeconomic returns to schooling as in Hall and C Jones (1999), and by using my way of measuring human capital (here, I assume that differences in the human capital aggregator reflect differences in human capital; in the next section, I discuss the alternative interpretation that it

[15] This estimate is slightly above the $50\%-70\%$ interval discussed in the review article by Hsieh and Klenow (2010a) and the 70% in the latest handbook chapter written by C Jones (2015). Four percentage points of the difference can be explained by the Mincerian method attributing 14% to human capital. I also use a later version of the Penn World Table and updated data.

reflects skill-augmenting technology shifters).[16] Granted, it is a complex counterfactual to ceteris paribus increase the skill levels of Tanzanian workers to those of US workers – including specialized computer engineers, world-class researchers, the whole range of the US medical profession, financial experts, corporate lawyers, and so forth. However, the exercise illustrates the effect of varying the method of aggregating human capital.

I start with the traditional development accounting approach. For 2010, the Barro-Lee data estimates Tanzanian average schooling levels to be 5.81 years, and US average schooling levels to be 13.18 years, a difference of approximately 7.5 years. Using the Mincerian return function from Hall and C Jones (1999) and Caselli (2005), these schooling differences translate into an approximately 0.6 log point difference in human capital. Using the aggregate production function (6), log Tanzanian GDP per worker increases by the same amount.

This example illustrates that traditional development accounting does not attribute a dominant role to human capital in explaining income differences across countries. Even if Tanzania increases the skill levels of its workforce all the way to US skill levels, GDP per worker only increases by 0.6 log points, or to \$4675. After this change in skill levels, Tanzanian income levels would not move higher than somewhere between Senegal and Bangladesh.

In contrast, if differences in the aggregator G reflect human capital differences, my method estimates that there is an approximate 2.6 log point difference in human capital between the US and Tanzania. After increasing the skill levels of the Tanzanian workforce, Tanzania would have a GDP per worker of approximately $\$36,000$, making it approximately as rich as Russia. The lower TFP of Tanzania would still make it substantially poorer than the US (with a GDP per worker of $\$93,000$), but the change would make it an upper middle income country.

4 Interpretation of mechanism: High efficiency of skilled labor

4.1 Mechanism

Section 3.3 showed that my method of aggregating human capital attributes a much smaller share of income differences to uniform TFP-differences than traditional development accounting does. Instead, the important difference between rich and poor countries is a large difference in the efficiency of skilled labor. Figure 6 shows the relationship between log GDP per worker and the efficiency of skilled labor according to the traditional development accounting method which equates relative skilled labor efficiency with the skilled wage premium, and according to my method, which also allows for differences in the relative price of skilled services (in both cases, I normalize log US skilled labor efficiency to 0).

The figure shows that traditional development accounting methods actually estimate that poor

[16] I use the method of Hall and C Jones (1999) instead of equation (10). In this setting, they yield very similar results, but it is easier to explain the method of Hall and C Jones (1999) in this context.

countries have a somewhat higher efficiency of skilled labor than rich countries. This reflects higher skilled wage premia in poor countries. The picture is different when we adjust for relative service price differences. Now, the efficiency of skilled labor is about four and a half log points lower in poor compared to in rich countries. The large estimated efficiency differences reflect large estimated differences in relative skilled service prices. The relative price of skilled services and the relative efficiency of skilled labor are related through

$$\frac{w_s}{w_u} = \frac{Q_s}{Q_u}\frac{r_s}{r_u},$$

where $\frac{w_s}{w_u}$ is the skilled wage premium. The trade data estimates suggest that the relative price of skilled services $\frac{r_s}{r_u}$ is 4-5 log points lower in rich countries. Skilled wage premia are also lower in rich countries, but only approximately one log point lower. This means that the relative efficiency of skilled labor is 3-4 log points higher in rich countries. My results follow from combining this finding with the 0.5 rich-poor log difference in the quality of unskilled labor. Intuitively, large efficiency differences are needed to reconcile moderate differences in skilled wage premia with large differences in trade patterns.

The large differences in the efficiency of skilled labor means that a smaller share of income differences are explained by differences in uniform efficiency levels, A. Indeed, traditional development accounting will in general overestimate the importance of uniform efficiency differences when rich countries have a higher efficiency of skilled labor (B Jones, 2014a). The reason is that traditional development accounting relies on the skilled wage premium to capture the output effect of improved efficiency of skilled labor. However, when skilled and unskilled labor services are imperfect substitutes, an improved efficiency of skilled labor will not increase the skilled wage premium one-for-one. Instead, improvements in skilled labor efficiency have two counteracting effects. First, there is a direct effect from higher efficiency to higher wages. Second, there is an indirect effect, as the relative price of skilled labour services decreases when the relative supply of skilled labor services increases. The strength of the second channel depends on the elasticity of substitution between skilled and unskilled labor services. In the limiting case of perfectly substitutable labour inputs, as in traditional development accounting, only the first channel is active.[17]

This bias in traditional development accounting can be illustrated in an economy where the human capital aggregator is Cobb-Douglas. The aggregator is:

$$h = u^{1-\beta}(Q_s s)^{\beta},$$

[17] For further discussions of the role of skilled labor efficiency differences and human capital accounting, see B Jones (2014a) and B Jones (2014b).

Figure 6: Log GDP per worker and log efficiency of skilled workers

and the relative price of skilled and unskilled labor services is

$$\frac{r_s}{r_u} = \frac{\beta}{1-\beta}\frac{u}{Q_s s}.$$

The relative price of skilled labor services is inversely proportional to the quality of skilled labor. In this setting, the skilled wage premium is actually independent of the quality of skilled labor Q_s, as an increase in Q_s is precisely offsets by a fall in the relative price of skilled labor services. If a country increases its quality of skilled labor, traditional development accounting methods will not estimate any change in Q_s, and will attribute all output gains to TFP. The Cobb-Douglas functional form makes this effect stark, but the mechanism is general.

4.2 Interpretation of skilled-labor efficiency differences

The previous section showed that the log efficiency of skilled labor Q_s is approximately 4 higher in rich countries than in poor countries. This corresponds to rich countries having approximately 50 times higher efficiency of skilled labor. In this section, I discuss the interpretation of these efficiency differences.

If we retain the assumption from traditional development accounting that technology differences across countries are skill neutral, then skilled-labor efficiency differences reflect a higher human capital among skilled workers in rich countries. Under this interpretation, a majority of the income differences across countries are explained by human capital differences.

The human capital interpretation can in turn take two different forms depending on which of the two different interpretations of Q_s from Section 3 that we use. Either, we interpret skilled labor as being internally undifferentiated. This means that different types of skilled workers are perfectly substitutable, which, in turn, means that quality differences in skilled labor human capital reflects a difference in the average amount of skilled labor services delivered by skilled workers. Alternatively, we interpret the skilled labor efficiency level Q_s as arising from an aggregation of heterogeneous skilled labor services, in which case Q_s will reflect more complicated complementarity and substitutability patterns.

The human capital interpretation is made in B Jones (2014a). In a complementary paper (B Jones, 2014b), Jones also explains how skilled labor efficiency differences can arise from human capital differences due to the aggregation of heterogeneous types of skilled services. This happens due to specialization among skilled workers allowing for higher worker efficiency at particular tasks (rather than skilled workers being uniformly better at all skilled tasks).

If we relax the assumption of neutral technology differences, an alternative explanation is that skilled labor efficiency differences reflect skill-specific technology differences. This is the interpretation made in Caselli and Coleman (2006) and Caselli (2016). Under this interpretation, technology differences are still more important than human capital differences, but it is a different form of technology differences than the uniform TFP differences found in traditional development accounting. In particular, theories of technology differences should explain why technology in rich countries selectively make skilled workers more efficient.

Thus, differences in skilled labor efficiencies can stem from at least three different mechanisms. Either, they stem from human capital differences of the form that the average skilled worker in a rich country supplies more skilled labor services, or they stem from human capital differences of the form that the aggregation of heterogeneous skilled workers in rich countries lead to a larger aggregate flow of skilled labor services per worker. Third, the skilled labor efficiency differences might reflect differences in skill-augmenting technologies across rich and poor countries.

With a flexible specification of variations in technology and skilled labor human capital across countries, it is not possible to distinguish between these three interpretations using only price and quantity data. Indeed, human capital quality and factor augmenting technology terms appear in the same way in production functions. Thus, they have the same implications for quantity and price data. Intuitively, price and quantity data alone cannot tell whether a worker is good at hammering, or has a good hammer. To discriminate between the interpretations, more theoretical structure or other sources of evidence are needed.

4.3 Using migration data to distinguish technology and human capital quality

A promising route to discriminate between the different interpretations is to exploit evidence from migration data. Ideally, migration provides a natural experiment to distinguish between human capital-based and technology-based explanations of income differences across countries, as migration data allows us to compare similar workers in two different environments with human capital kept constant. In light of this, wage increases at migration have been used to gauge the human capital component of income differences going back to Hendricks (2002). For a long time, a challenge in this literature has been the selection of migrants, but this concern has been addressed by new data collection efforts in Hendricks and Schoellman (2017), which have used data from the New Immigrant Survey (NIS) to construct pre- and post-migration earnings of US immigrants.

In this section, I analyze how migration wage data can be used to discriminate between different interpretations of skilled labor efficiency differences. The first conclusion is negative: with imperfectly substitutable labor services, varying relative prices of different labor tasks raise a number of complicated challenges in using migration data to correctly identify human capital differences. However, even though a full solution of these challenges lies beyond the scope of this paper, I show that it is possible to use the summary statistics of wage changes at migration, as provided in Hendricks and Schoellman (2017), to obtain some simple lower bounds on the importance of human capital in explaining skilled labor efficiency differences. According to this quantification, human capital quality differences contribute at least a quarter of the skill-specific efficiency differences observed between the US and countries with incomes between 1/16 and 1/8 of US levels.

4.3.1 Interpreting migrant wage data with imperfect substitutability

The standard approach in the literature for estimating human capital from migration data has relied on an assumption of perfect substitutability for the main quantitative results (Hendricks, 2002; Hendricks and Schoellman, 2017). The assumption of perfectly substitutable labor services (combined with no capital-skill complementarity) simplifies the estimation of human capital from migration data, as perfect substitutability between labor services implies that the log wage of a worker can be decomposed into a location term and a human capital term (Hendricks and Schoellman, 2017). The change in wage at migration captures the difference in location term, and the residual difference in average wages across the two countries can be interpreted as a human capital term.

When labor services are imperfectly substitutable, it is less straightforward to use migrant wage data to infer human capital differences. The key issue is that with imperfect substitutability, countries will have different relative prices between different tasks. Thus, if there is a change in the wage of a worker upon migration, this need not reflect a change in technology, but it could also reflect a change in the relative prices facing the worker. Focusing on the relevant case for this paper, with skilled versus unskilled workers, this leads to three important challenges.[18]

First, there is a need to correct for the relative price of skilled and unskilled labor services across countries. Indeed, with different relative prices of skilled and unskilled labor services, wages of workers will change upon migration even if there are no technology differences. For example, even in the absence of technology differences, the relative scarcity of unskilled labor services in rich countries means that unskilled wages will increase upon migration to rich countries. This means that it is not valid to interpret wage changes at migration as reflecting technology and capital differences when there is imperfect substitutability.

Second, the potential for occupational switching might bias the results. If workers select into occupations based on comparative advantage in different tasks (as, for example, in Acemoglu and Autor, 2011), then workers will switch occupations upon migration reflecting a changing comparative advantage. In particular, skilled workers going from poor to rich countries will be more likely to switch to an unskilled occupation, as the relative price of unskilled labor services is higher. Intuitively, given the high relative price of unskilled labor services in the US, a moderately good programmer from a poor country might select into an unskilled occupation upon moving to the US. The potential of switching occupation according to comparative advantage increases the wage gains of migration.

Third, if the observed efficiency differences in skilled labor reflect aggregation of heterogeneous types of skilled labor services as in B Jones (2014b), the analysis of migrant data needs to take into account the complementarity and substitutability patterns of different types of skilled and unskilled workers implicit in the aggregator of skilled services. For example, if skilled workers perform specialized tasks and produce by matching with other workers, then an increased wage upon migration to a rich country could reflect a higher human capital of co-workers, rather than different technologies. Conversely, a fall in the wage for a skill worker moving to a poor country can reflect a lack of complementary skilled workers.

4.3.2 Providing bounds on human capital using migrant wage data

In light of these challenges, a complete quantification of human capital versus technology from migration wage data would require us to take a stand on the skilled labor aggregator (including potential assortative matching between skilled workers), and construct a theoretically motivated way of correcting for occupational switching. Such a quantification lies beyond the scope of this paper. Nevertheless, if we interpret the observed wage increases from Hendricks and Schoellman (2017) as reflecting the wage gains of skilled migrants going to the US, it is possible to use their summary statistics of wage gains to provide a rudimentary lower bound for the importance of

[18] For more discussions on interpreting migrant wage data with imperfect substitutability, see B Jones (2014a) and B Jones (2014b).

human capital in explaining skilled labor efficiency differences.[19]

To do this, I decompose skilled labor efficiency $Q_{i,s} = H_{i,s}A_{i,s}$ into a human capital term $H_{i,s}$ and a skill-specific technology term $A_{i,s}$ (using the interpretation that skilled labor efficiency differences reflect differences in the average human capital quality/technology of all skilled workers, and not aggregation of heterogeneous skilled labor services). Under this interpretation, the wage of a skilled worker in country i under competitive markets, and the assumed aggregate production function, is

$$w_{i,s} = (1-\alpha)\left(\frac{K_i}{Y_i}\right)^{\frac{\alpha}{1-\alpha}} A_i H_{i,s} A_{i,s} G_{i,s}, \tag{11}$$

where A_i is a uniform TFP-shifter, and $G_{i,s}$ reflects the partial derivative of the human capital aggregator G with respect to skilled labor in country i.

Writing $k_i = \frac{K_i}{Y_i}$ for the capital-output ratio, and using that workers keep their human capital upon migration, the wage gain for a skilled worker from migrating to the US can be written as

$$\frac{w^m_{US,s}}{w^m_{i,s}} = \left(\frac{k_{US}}{k_i}\right)^{\frac{\alpha}{1-\alpha}} \frac{A_{US}}{A_i} \frac{A_{US,s}}{A_{i,s}} \frac{G_{US,s}}{G_{i,s}}. \tag{12}$$

That is, the wage gain is a product of the relative capital intensity raised to $\frac{\alpha}{1-\alpha}$, the relative uniform TFP differences, the relative skill-biased technology terms, and the relative prices per units of skilled labor services in the two countries. All variables apart from the relative skill-biased technology terms are measurable. The relative uniform TFP differences are estimated in the development accounting exercises. Furthermore, since $w_{i,s}$ and $Q_s = H_{i,s}A_{i,s}$ are observable, the partial derivative $G_{i,s}$ can be calculated from equation (11). This allows us to back out $\frac{A_{US,s}}{A_{i,s}}$ from equation (12).

To perform the decomposition, I analyze the role of skill-biased technology versus human capital for the countries with income levels between 1/16 and 1/8 of US income levels. For this collection of countries, I use the reported wage gain $w^m_{i,s}/w^m_{US,s}$ of 2.8 times from Table 2 in Hendricks and Schoellman. I calculate the capital-output ratio using the Penn World Table. To calculate the partial derivative of the labor aggregator, I use a model consistent skilled wage level:

$$w_s s + w_u u = (1-\alpha) \Leftrightarrow w_s = \frac{w_s}{w_u} \frac{(1-\alpha)y}{u + \frac{w_s}{w_u} s},$$

which can be calculated from the skilled wage premium, the labor share of output per worker, and the traditional development accounting human capital measure. All of these objects are calculated

[19] The assumption that wage gains reflect those of skilled workers is based on the very positive selection of migrants in Hendricks and Schoellman (2017), the data of which is based on a survey of green card holders. Immigrants from the poorest countries had pre-migration wages four times as high as the average workers in their home countries, and only one migrant from the poorest sample worked in forestry and agriculture. Insofar some of the workers are unskilled, we will likely overestimate the wage gains of skilled migrants, and underestimate the importance of human capital.

in the development accounting exercise. Using this measure of $w_{i,s}$, I can calculate $G_{i,s}$ from equation (11) using that A_i and $Q_s = A_{i,s}H_{i,s}$ were both calculated in the development accounting exercise.[20]

The resulting role for human capital is likely to be an underestimate because the method neglects the possibility of occupational switching and complementarity between skilled workers. As workers usually switch to more unskilled occupations when moving to rich countries (approximately two thirds of the sample from poor countries in Hendricks and Schoellman (2017) switch to a lower paying profession upon moving to the US), observed wages are likely higher than they would have been had they been forced to work in skilled occupations. The neglect of complementarity patterns also means that we attribute the effect of matching with higher skilled workers to technology, even though this can appropriately be called a human capital effect.

The results are displayed in Table 6, with the columns representing different values of the trade elasticity σ. The case $\sigma = \infty$ represents the traditional development accounting assumption of perfectly substitutable labor services (an infinite trade elasticity implies that relative effective service prices $\frac{r_s}{r_u} \doteq \frac{G_s}{G_u}$ are constant across countries).

The first line shows that the wage increases on average 2.8 times for a worker going to the US from countries with 1/8 to 1/16 of US income levels. The next four rows decompose this wage increase into a contribution from capital intensity, a uniform technology difference, a difference in the price of skilled labor services, and a difference in skill-specific technology (which is backed out as a residual).

The Q_s-row shows the relative estimated skill-specific technology differences. The second to last row shows which share or skill-specific efficiency differences Q_s that is due to technology A_s. The last row shows the share of total efficiency differences of skilled workers AQ_s that is due to technology AA_s. In both cases, the share is expressed as a log share, i.e. $\frac{\Delta \log(A_s)}{\Delta \log(Q_s)}$ and $\frac{\Delta \log(AA_s)}{\Delta \log(AQ_s)}$ respectively.

The table shows that one quarter of skill-specific efficiency differences are due to technology for $\sigma = 10$. The capital intensity and uniform technology differences explain relatively little of the wage gains, reflecting modest differences in the capital output ratios, and, for $\sigma = 10$, small uniform technology shifters. Furthermore, the estimates suggest that the price of skilled labor services are considerably *lower* in the US compared to in poor countries, which means that large skill-specific technology shifters $\frac{A_{s,US}}{A_{s,poor}}$ are required to explain the wage gains of migrants.

As σ increases, the share attributable to technology falls. The reason is that a higher σ implies smaller differences in the skilled service price G_s, which lowers the amount of skill-specific technology differences required to explain the wage increases of migrants. However, as a larger σ implies larger

[20] Since the observed gains from migration represents a collection of countries, I regress each country level variable on log GDP per worker and take the predicted value given that a country has an 11.9 times lower GDP per worker than the US, reflecting the average GDP per worker gap in the migrant group.

uniform TFP differences as well, there is a smaller effect on the technology share of total efficiency differences of skilled workers.

The last column shows the results under the assumption of perfect substitutability. In line with traditional development accounting, there are large uniform efficiency differences: the uniform labor efficiency in the US is 8 times larger than in the poor countries. Since the skill prices are the same in the US and the poor countries, the skill-specific residual technology term becomes less than 1, i.e. the US has a lower skill-specific technology level. This echoes the findings in Hendricks and Schoellman (2017), who find that wage increases for migrants are smaller than what would be predicted give the uniform technology differences found in traditional development accounting. We also see that the skill-specific efficiency Q_s is lower in the US, reflecting the lower skilled wage premium in the US. Given that skill-specific efficiency is lower in the US, it makes less sense to talk about the share of skill-specific efficiency differences that are explained by technology. However, we can see that approximately 50% of overall efficiency differences are explained by technology. This is close to the number found in Hendricks and Schoellman (2017), who use the migration data to conduct development accounting under the assumption of perfect substitutability.

Table 6: Decomposition of wage changes at migration

	$\sigma = 10$	$\sigma = 15$	$\sigma = 20$	$\sigma = \infty$
$w^m_{s,US}/w^m_{s,poor}$	2.80	2.80	2.80	2.80
$\left(\frac{K_{US}/Y_{US}}{K_{poor}/Y_{poor}}\right)^{\frac{\alpha}{1-\alpha}}$	1.21	1.21	1.21	1.21
A_{US}/A_{poor}	1.28	2.49	3.41	8.34
$G_{s,US}/G_{s,poor}$	0.10	0.23	0.34	1.00
$A_{s,US}/A_{s,poor}$	18.13	4.08	2.01	0.28
$Q_{s,US}/Q_{s,poor}$	45.22	10.17	5.02	0.69
$\frac{\Delta \log(A_s)}{\Delta \log(Q_s)}$	0.76	0.61	0.43	
$\frac{\Delta \log(AA_s)}{\Delta \log(AQ_s)}$	0.77	0.72	0.68	0.48

5 Robustness and consistency checks

Here, I present various robustness and consistency checks of my results. In Section 5.1, I analyze how sensitive my estimates of relative skilled service prices are to varying underlying assumptions and parameters. In Section 5.2, I test whether my estimates of relative skilled service prices are consistent with estimates based on unit production cost data when such data are available. In Section 5.3, I analyze how my development accounting exercise is affected when I change the measurement of skilled wage premia, and how it is affected when I exclude very poor countries and oil producing countries from the analysis. The discussion of each robustness check is brief, and

Appendix D provides more detailed descriptions and discussions of the robustness checks.

Across a wide range of specifications and parameter values, the conclusion holds that the role of uniform efficiency differences is much smaller as compared to in findings based on traditional development accounting methods. Furthermore, for countries where both trade data and unit cost data are available, the two types of analyses give similar results. Excluding the poorest countries and oil producing countries decreases the importance of uniform efficiency differences.

5.1 Sensitivity of relative skilled service price estimates

I estimate the relative price of skilled services using the regression specification (5). In this section, I test the sensitivity of my relative price estimates to variations in the price elasticity of trade, the set of control variables, the functional form of the underlying industry production functions, and the presence of zero trade flows.

Table 7 shows how my development accounting results change when I change the elasticity of trade σ. Variations in σ are quantitatively important, and a larger σ means a lower importance of variations in the human capital aggregator. The intuition is that a larger σ means that less relative unit cost differences are needed to explain the trade data. This reduces the estimated differences in relative skilled service prices which, in turn, imply a reduction in the estimated quality differences of skilled labor. Even though a larger σ implies a smaller role for the human capital aggregator, the estimated importance of the human capital aggregator term for $\sigma = 15$ is still 4.5 times as large as that found using traditional development accounting methods. When the trade elasticity is $\sigma = 5$, variations in the human capital aggregator more than explain income differences across countries, implying lower uniform efficiency levels in the US compared to in poor countries. In Appendix D.1, I discuss the effect of allowing trade elasticities to be different across industries.

A second potential problem in regression (5) is omitted variables in the specification of unit costs. The regression specification assumes that variations in relative unit costs are only driven by variations in relative factor service prices. If there are other determinants of unit costs correlated with relative factor service prices, there will be an omitted variable bias. I test for the importance of an omitted variable bias by controlling for potential determinants of unit costs apart from relative factor service prices. In particular, I allow there to be a country-specific penalty on external financing and/or contracting. These penalties increase the log unit cost of an industry in proportion to the financial dependence and/or contracting dependence of the industry. To measure financial dependence and contracting dependence at an industry level, I use measures similar to those developed by Rajan and Zingales (1998) and Nunn (2007), respectively. The results are presented in Table 8. Including a term for contracting sensitivity does not affect the importance of human capital, and including a term for financial sensitivity decreases the importance of human capital from 65% to 51%. In Appendix D.2, I describe the definition of industry financial and contracting sensitivities, and how they are included in my regression.

A third potential problem in regression (5) is a second-order bias in the log-linearization of unit costs. The regression specification is based on log-linearizing unit costs around the US cost structure. This log-linearization is exact if the industry production functions are Cobb-Douglas. If the industry production functions are not Cobb-Douglas, there will be a second-order bias as industry factor shares vary with relative factor service prices. I analyze how my results change if industry production functions are CES with a common elasticity of substitution $\xi \neq 1$. I test for this bias by creating model generated unit costs from a model where industry production functions are CES. I run my regression specification (5) on the model generated data and look for the price differences in the model such that my regressions yield similar results on actual and model generated data. This procedure allows me to gauge the bias in my baseline estimates. Table 9 shows the development accounting results for different assumed values of ξ. Appendix C.3 explains the environment, the estimation method, the results, and the economic intuition in greater detail.

A fourth potential problem in regression (5) is zero trade flows. Approximately 62% of the bilateral trade flows on the NAICS four-digit level are zero. Given that regression (5) is defined for log trade flows, export flows of value zero are dropped, which risks biasing my estimates. One way of gauging the effects of excluding zeros is to run the regression on a higher level of aggregation, which reduces the numbers of zeros. Figure 7 shows the estimated relative skilled service prices when I run the regression on four-digit and three-digit manufacturing industries. The three-digit estimates are less precisely estimated as there are only 21 industries instead of 84. However, there is a very similar relationship between log income per worker and log estimated relative skilled service prices.

Table 7: Contribution of factors and TFP to income differences: different σ

	Baseline ($\sigma = 10$)	$\sigma = 5$	$\sigma = 15$
Capital	0.08	0.08	0.08
Human capital – trad.	0.12	0.12	0.12
Human capital – new	0.65	1.33	0.45
TFP – trad.	0.79	0.79	0.79
TFP – new	0.26	-0.4	0.46
Log TFP diff. – trad.	2.54	2.54	2.54
Log TFP diff. – new	0.85	-1.3	1.48
TFP-diff. reduction	67%	153%	42%
Elasticity of subst.	1.27	1.10	1.46

Table 8: Contribution of factors and TFP to income differences: different control variables

	Baseline	Contracting	Financing	Both
Capital	0.08	0.08	0.08	0.08
Human capital – trad.	0.12	0.12	0.12	0.12
Human capital – new	0.65	0.63	0.51	0.51
TFP – trad.	0.79	0.79	0.79	0.79
TFP – new	0.26	0.27	0.40	0.40
Log TFP diff – trad.	2.54	2.54	2.54	2.54
Log TFP diff – new	0.85	0.89	1.28	1.28
TFP-diff. reduction	67%	66%	50%	50%
Elasticity of subst.	1.27	1.28	1.35	1.35

Table 9: Contribution of factors and TFP to income differences: different ξ.

	$\xi = 0.6$	$\xi = 0.8$	$\xi = 1$	$\xi = 1.2$	$\xi = 1.4$
Capital	0.07	0.07	0.07	0.07	0.07
Human capital – trad.	0.12	0.12	0.12	0.12	0.12
Human capital – new	0.65	0.62	0.63	0.68	0.84
TFP – trad.	0.80	0.80	0.80	0.80	0.80
TFP – new	0.26	0.29	0.28	0.23	0.07
Log TFP diff – trad.	2.56	2.56	2.56	2.56	2.56
Log TFP diff – new	0.85	0.95	0.92	0.75	0.24
TFP-diff. reduction	67%	63%	65%	71%	91%
Elasticity of subst. η	1.36	1.39	1.38	1.34	1.26

5.2 Consistency between trade data and unit cost data

In Section 2, I used trade data to substitute for missing unit cost data. However, the Groningen Growth and Development Center has constructed a unit cost measure for 34 industries across 42 countries. A natural consistency check is whether my trade data method yields similar conclusions as a unit cost based method on this set of countries.

The GGDC index covers both tradable and non-tradable industries, and manufacturing as well as services. Using the GGDC data set, I can run a unit cost regression to estimate relative factor service prices.[21]

$$\log(c_i^k) = \delta_i + \mu_k + \sum_{f=2}^{F} \alpha_{US,f}^k \tilde{\beta}_{i,f}.$$

Here, δ_i is a country-fixed effect, μ_k is an industry-fixed effect, and $\tilde{\beta}_{i,f}$ identifies the country-factor

[21] In Appendix D.3, I derive this regression specification, and provide more details on all measurements.

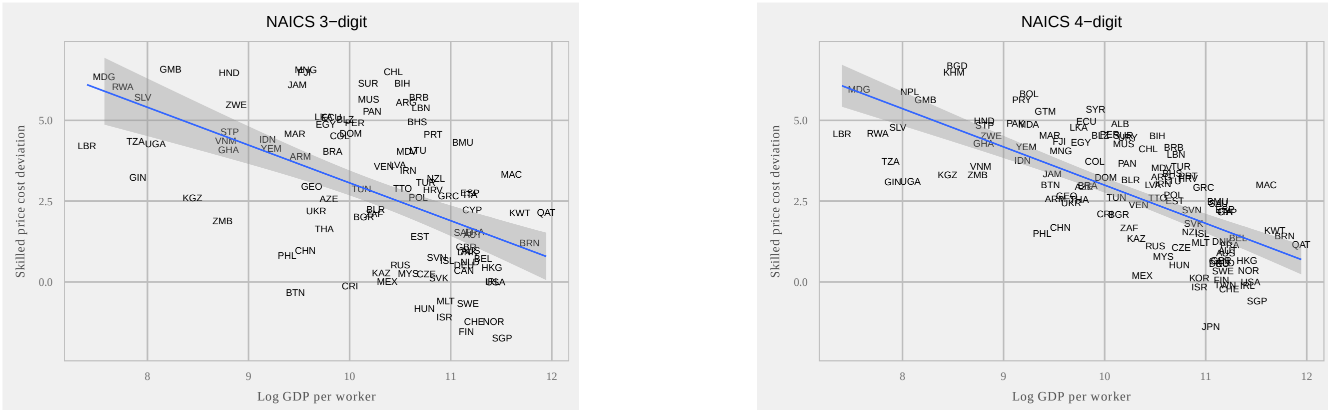


Figure 7: Estimated skill price differences with $\sigma = 10$. NAICS 3-digit and 4-digit.

relative factor service price differences. In Figures 8 and 9, I plot the relationship between estimated log relative skilled service prices and log GDP per worker, both with country names and with error bars. The results have larger standard errors than the trade based estimates. This reflects the lower number of industries. However, just like the trade based estimates, they exhibit a strong negative correlation with log GDP per worker. The slope parameter of log relative skilled service prices on log GDP per worker is -1.19 using the unit cost data, and -1.53 using the trade data method for the same set of countries. These estimates are similar, and I cannot reject that the two slopes are equal, even when I do not take into account the large standard errors on the unit cost based estimates. Thus, when both types of data exist, the trade data method and the unit cost method paint a similar picture of the relationship between relative skilled service prices and income per worker.

5.3 Further robustness tests of development accounting

In this section, I consider further robustness tests of my development accounting exercise. I analyze how my results change when I exclude the poorest countries and when I exclude oil countries, and I analyze how my results change when I change the measurement of skilled wage premia.

My baseline analysis includes all countries with available trade data, ILO data, and PWT data. Hence, my analysis includes very poor countries and countries with significant oil revenues. Including these countries can be problematic as I use manufacturing trade data to estimate the relative price of skilled services prices. Very poor countries have limited manufacturing trade, and the trade patterns of oil countries are primarily determined by their oil endowment. In Table 10, I show the results when I exclude oil countries and countries with a log GDP per worker of less than 9 in 2010 (corresponding approximately to Ghanaian income levels). Excluding these countries considerably expands the role of the human capital aggregator, and when both sets of countries are excluded, no uniform TFP differences are needed to explain the income differences among the

Figure 8: Skilled price deviation estimates vs log GDP per worker using unit cost data

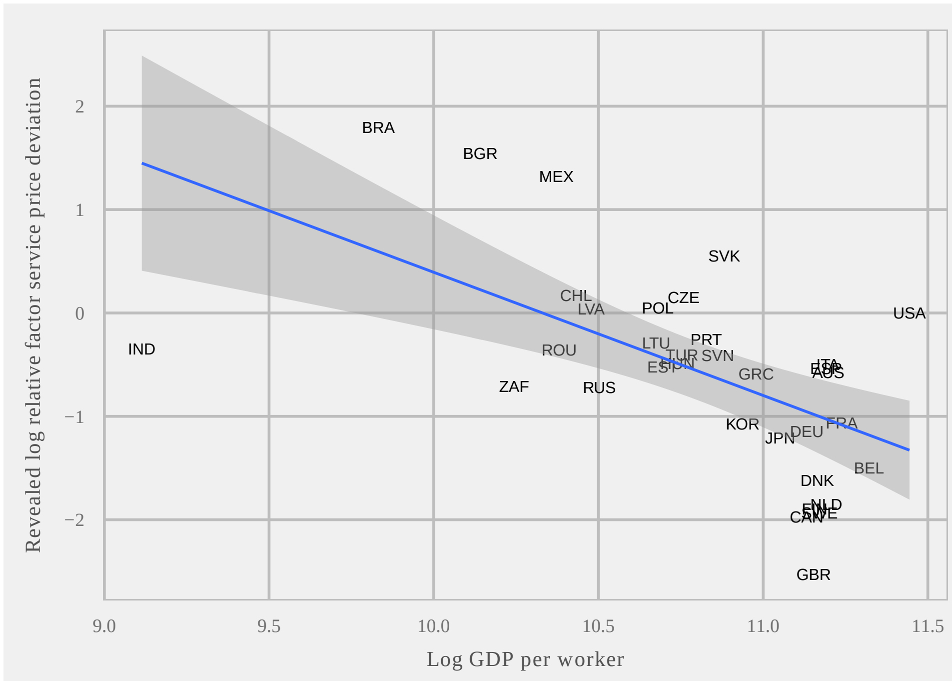
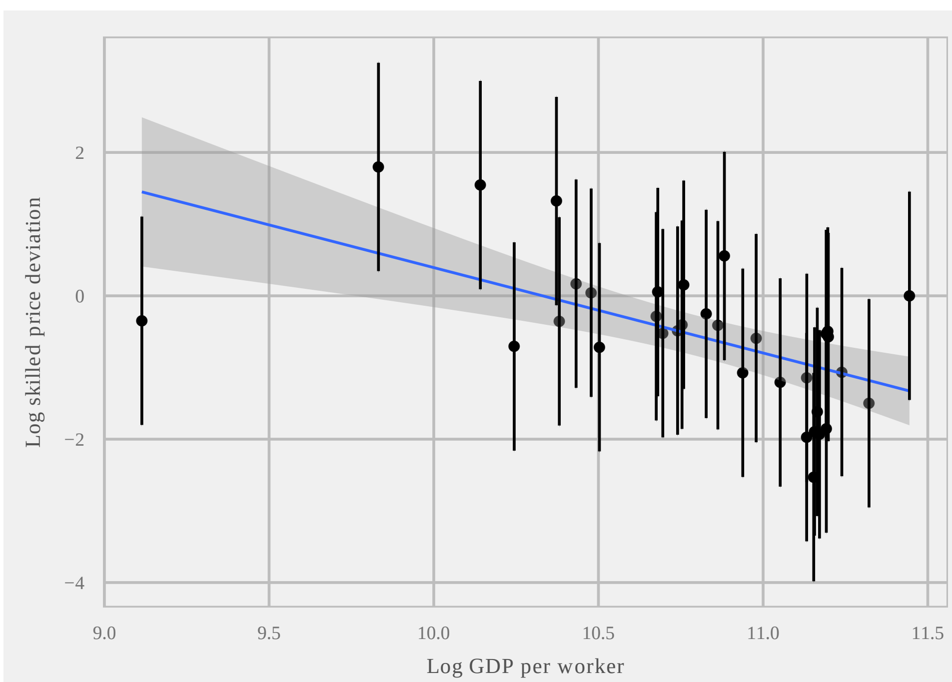


Figure 9: Skilled price deviation estimates vs log GDP per worker using unit cost data



remaining countries.

I also analyze the robustness of my results to different measurements of skilled wage premia. My skilled wage premia measures are based on limited ILO data, and I want my estimates to be robust to systematic errors in the data on skilled wage premia in poor countries. I am particularly concerned that my measures understate skilled wage premia in poor countries due to the difficulty in measuring the wages of self-employed workers and subsistence farmers. My skilled wage premia measures are based on using a linear relation between log GDP per worker and log skilled wage premia. To test how my results depend on skill premia, I consider how my results change if I allow for a steeper relation between country income and log skilled wage premia keeping rich country skilled wage premia constant. I redo my analysis for different values of the income-skill premia slope $\gamma \leq 0$. The results are presented in Table 11.

Variations in the posited slope between skilled wage premia and country income have little effect on the estimated importance of the human capital aggregator. The reason is that two effects counteract each other. Higher skilled wage premia in poor countries reduce the estimated skill-biased quality differences, but they simultaneously reduce the estimated elasticity of substitution between skilled and unskilled workers. These two effects have opposite consequences for the estimated importance of the human capital aggregator, and they approximately offset each other. Intuitively, there are two cases. If skilled wage premia are very high in poor countries, it suggests that skilled services are difficult to replace, and poor countries are poor because they have few skilled services. Uniform efficiency differences are less important. If skilled premia are very low in poor countries, large efficiency differences among skilled workers are needed to fit the trade data. Once more, the conclusion is that skilled labor efficiency differences are relatively more important than uniform efficiency differences in accounting for income differences.

Table 10: Contribution of factors and TFP to income differences: different excluded countries

	Baseline	No v. poor	No oil	Neither
Capital	0.08	0.05	0.08	0.06
Human capital – trad.	0.12	0.10	0.13	0.12
Human capital – new	0.65	0.85	0.68	0.94
TFP – trad.	0.79	0.83	0.77	0.80
TFP – new	0.26	0.08	0.22	-0.0
Log TFP diff – trad.	2.54	2.67	2.49	2.58
Log TFP diff – new	0.85	0.27	0.72	-0.0
TFP-diff. reduction	67%	90%	72%	102%
Elasticity of subst.	1.27	1.20	1.27	1.20

Table 11: Contribution of factors and TFP to income differences: different wage premia

Slope coefficients (baseline = -0.12)	Baseline	0.0	-0.2	-0.4
Capital	0.08	0.08	0.08	0.08
Human capital – trad.	0.12	0.12	0.12	0.12
Human capital – new	0.65	0.62	0.65	0.66
TFP – trad.	0.79	0.79	0.79	0.79
TFP – new	0.26	0.29	0.26	0.25
Log TFP diff – trad.	2.54	2.54	2.54	2.54
Log TFP diff – new	0.85	0.95	0.85	0.81
TFP-diff. reduction	67%	63%	67%	68%
Elasticity of subst.	1.27	1.37	1.27	1.18

6 Concluding remarks

This paper has revisited development accounting when skilled and unskilled labor services are imperfect substitutes. It is known in the literature that under imperfect substitutability, traditional development accounting will overestimate the importance of uniform efficiency differences, and underestimate the importance of skill-specific efficiency differences. However, it is challenging to quantify this mechanism, as this requires us to measure the variation across countries in the efficiency-adjusted relative price of skilled and unskilled labor services, which is not directly observable.

In this paper, I have used evidence from international trade data to estimate the efficiency-adjusted relative price of skilled and unskilled labor services. The analysis suggests that skilled labor services are relatively cheap in rich countries. When these relative price estimates are integrated in a development accounting exercise, the required log uniform TFP differences between rich and poor countries fall by 66%. Instead, skill-specific efficiency differences become more important in explaining income differences across countries.

Compared to traditional development accounting, the importance of skill-specific efficiency differences suggests a different set of interpretations of income differences across countries. First, if skilled efficiency differences are due to human capital differences, it suggests that human capital differences among skilled workers can explain a large share of world output differences. This, in turn, warrants a greater focus on theories of skill acquisition. Potentially interesting areas include the quality of higher education, the opportunities for more extensive specialization, and the incentives and efficiency of on-the-job training. Alternatively, the efficiency of skilled labor might be driven by skill-specific technology shifters, in which case theories of technology differences should place a larger emphasis on why technology differences selectively make skilled labor more efficient in rich countries. This suggests a shift away from general TFP explanations toward more specific theories of technology differences. For example, when studying technology diffusion, it might be warranted to study whether barriers to technology diffusion specifically prevent the diffusion of technologies that are complementary to skilled workers.

There is further work to be done both on the size and interpretation of skilled labor efficiency differences. Starting with the size of skill-biased efficiency differences, it is worth exploring improvements and alternatives to the current trade data based method. The benefit of using trade data is that, lacking cross-country comparable producer price indices, trade data contain implicit information about quality adjusted unit costs across industries, which makes trade data useful for estimating cross-country industry-specific productivity differences. However, there are also drawbacks to using trade data. First, it requires us to place structural assumption on how trade flows are determined. In particular, the relevant price elasticity of trade is challenging to estimate. Second, when we want to use the trade estimates in development accounting, we need to extrapolate from tradable manufacturing products to the rest of the economy. Potential future work includes using results from the literature on selection of firms into trade to quantify the potential bias of using trade-based estimates for the overall economy. The trade data analysis could also be complemented with alternative methods, for example a more detailed analysis of the wage structure of skilled workers in poor countries to identify the prices of particular skills.

In terms of interpretation, we noted that a number of different sources of skilled labor efficiency differences are isomorphic in price and quantity data. This makes it challenging to identify whether skilled labor efficiency differences are due to differences in human capital, technology, or some combination of the two. The migration analysis in this paper provided some lower bounds on the importance of human capital. However, this analysis neglected the potential for occupational switching, or the existence of complementarities and substitutabilities between different types of skilled workers. Thus, in order to better quantify the sources of skill-biased efficiency differences, an interesting avenue for future work is to develop ways of using migration data in combination with disaggregated wage data to estimate how skilled labor services are aggregated.

References

Acemoglu, D. (2007). Equilibrium Bias of Technology. *Econometrica*, 75(5):1371–1409.

Acemoglu, D., Antràs, P., and Helpman, E. (2007). Contracts and Technology Adoption. *American Economic Review*, 97(3):916–943.

Acemoglu, D. and Autor, D. (2011). Chapter 12 Skills, Tasks and Technologies: Implications for Employment and Earnings. In *Handbook of Labor Economics*, volume 4, pages 1043–1171.

Acemoglu, D. and Ventura, J. (2002). The World Income Distribution. *The Quarterly Journal of Economics*, 117(2):659–694.

Acemoglu, D. and Zilibotti, F. (2001). Productivity Differences. *The Quarterly Journal of Economics*, 116(2):563–606.

Anderson, J. E., Anderson, and James (1979). A Theoretical Foundation for the Gravity Equation. *American Economic Review*, 69(1):106–16.

Anderson, J. E. and van Wincoop, E. (2003). Gravity with Gravitas: A Solution to the Border Puzzle. *American Economic Review*, 93(1):170–192.

Barro, R. J. and Lee, J. W. (2013). A new data set of educational attainment in the world, 19502010. *Journal of Development Economics*, 104:184–198.

Bartelsman, E. J. and Gray, W. (1996). The NBER Manufacturing Productivity Database.

Broda, C., Weinstein, D., Broda, C., and Weinstein, D. (2006). Globalization and the Gains from Variety. *Quarterly Journal of Economics*, 121:541–585.

Caselli, F. (2005). Chapter 9 Accounting for Cross-Country Income Differences. *Handbook of Economic Growth*, 1:679–741.

Caselli, F. (2016). *Technology Differences Over Space and Time*. Princeton University Press.

Caselli, F. and Ciccone, A. (2013). The contribution of schooling in development accounting: Results from a nonparametric upper bound. *Journal of Development Economics*, 104:199–211.

Caselli, F. and Coleman, W. J. (2006). The World Technology Frontier. *American Economic Review*, 96(3):499–522.

Chor, D. (2010). Unpacking sources of comparative advantage: A quantitative approach. *Journal of International Economics*, 82(2):152–167.

Ciccone, A. and Papaioannou, E. (2009). Human Capital, the Structure of Production, and Growth. *Review of Economics and Statistics*, 91(1):66–82.

Costinot, A., Donaldson, D., and Komunjer, I. (2011). What Goods Do Countries Trade? A Quantitative Exploration of Ricardo's Ideas. *The Review of Economic Studies*, 79(2):581–608.

Cuñat, A. and Melitz, M. J. (2012). Volatility, Labor Market Flexibility, and the Pattern of Comparative Advantage. *Journal of the European Economic Association*, 10(2):225–254.

Eaton, J. and Kortum, S. (2002). Technology, Geography, and Trade. *Econometrica*, 70(5):1741–1779.

Erosa, A., Koreshkova, T., and Restuccia, D. (2010). How Important Is Human Capital? A Quantitative Theory Assessment of World Income Inequality. *Review of Economic Studies*, 77(4):1421–1449.

Gaulier, G. and Zignago, S. (2010). BACI: International Trade Database at the Product-Level (the 1994-2007 Version). *SSRN Electronic Journal*.

Gollin, D. (2002). Getting Income Shares Right. *Journal of Political Economy*, 110(2):458–474.

Hall, R. E. and Jones, C. I. (1999). Why do Some Countries Produce So Much More Output Per Worker than Others? *The Quarterly Journal of Economics*, 114(1):83–116.

Head, K. and Mayer, T. (2014). Gravity Equations: Workhorse,Toolkit, and Cookbook. In *Handbook of International Economics*, volume 4, pages 131–195. Elsevier B.V.

Hendricks, L. (2002). How Important Is Human Capital for Development? Evidence from Immigrant Earnings. *American Economic Review*, 92(1):198–219.

Hendricks, L. and Schoellman, T. (2017). Human Capital and Development Accounting: New Evidence from Wage Gains at Migration.

Hsieh, C.-T. and Klenow, P. J. (2009). Misallocation and Manufacturing TFP in China and India *. *Quarterly Journal of Economics*, 124(4):1403–1448.

Hsieh, C.-T. and Klenow, P. J. (2010a). Development Accounting. *American Economic Journal: Macroeconomics*, 2(1):207–23.

Hsieh, C.-T. and Klenow, P. J. (2010b). Development Accounting. *American Economic Journal: Macroeconomics*, 2(1):207–223.

Inklaar, R. and Timmer, M. P. (2008). GGDC Productivity Level Database: International Comparisons of Output, Inputs and Productivity at the Industry Level. *GGDC Research Memorandum*.

Jones, B. F. (2014a). The Human Capital Stock: A Generalized Approach. *American Economic Review*, 104(11):3752–3777.

Jones, B. F. (2014b). The Knowledge Trap: Human Capital and Development Reconsidered.

Jones, C. (2015). The Facts of Economic Growth. Technical report, National Bureau of Economic Research, Cambridge, MA.

Katz, L. F. and Murphy, K. M. (1992). Changes in Relative Wages, 1963-1987: Supply and Demand Factors. *The Quarterly Journal of Economics*, 107(1):35–78.

Klenow, P. and Rodriguez-Clare, A. (1997). The Neoclassical Revival in Growth Economics: Has It Gone Too Far? Technical report.

Krugman, P. (1988). Differences In Income Elasticities and Trends in Real Exchange Rates. Technical report, National Bureau of Economic Research, Cambridge, MA.

Levchenko, A. A. and Zhang, J. (2016). The evolution of comparative advantage: Measurement and welfare implications. *Journal of Monetary Economics*, 78:96–111.

Manova, K. (2013). Credit Constraints, Heterogeneous Firms, and International Trade. *The Review of Economic Studies*, 80(2):711–744.

Manuelli, R. E. and Seshadri, A. (2014). Human Capital and the Wealth of Nations . *American Economic Review*, 104(9):2736–2762.

Mattsson, L.-G., Weibull, J. W., and Lindberg, P. O. (2014). Extreme values, invariance and choice probabilities. *Transportation Research Part B: Methodological*, 59:81–95.

Midrigan, V. and Xu, D. Y. (2014). Finance and Misallocation: Evidence from Plant-Level Data . *American Economic Review*, 104(2):422–458.

Morrow, P. and Trefler, D. (2017). Endowments, Factor Prices, and Skill-Biased Technology: Importing Development Accounting into HOV.

Nunn, N. (2007). Relationship-Specificity, Incomplete Contracts, and the Pattern of Trade. *The Quarterly Journal of Economics*, 122(2):569–600.

Nunn, N. and Trefler, D. (2015). Chapter 5: Domestic Institutions as a Source of Comparative Advantage. In *Handbook of International Economics*, volume 4, pages 263–315.

Oberfield, E. and Raval, D. (2014). Micro Data and Macro Technology. Technical report, National Bureau of Economic Research, Cambridge, MA.

Parente, S. L. and Prescott, E. C. (1999). Monopoly Rights: A Barrier to Riches. *American Economic Review*, 89(5):1216–1233.

Rajan, R. G. and Zingales, L. (1998). Financial Dependence and Growth. *American Economic Review*, 88(3):559–86.

Rauch, J. E. (1999). Networks versus markets in international trade. *Journal of International Economics*, 48(1):7–35.

Redding, S. and Venables, A. J. (2004). Economic geography and international inequality. *Journal of International Economics*, 62(1):53–82.

Restuccia, D. and Rogerson, R. (2008). Policy distortions and aggregate productivity with heterogeneous establishments. *Review of Economic Dynamics*, 11(4):707–720.

Romalis, J. (2004). Factor Proportions and the Structure of Commodity Trade. *American Economic Review*, 94(1):67–97.

Romalis, J. (2007). NAFTA's and CUSFTA's Impact on International Trade. *http://dx.doi.org/10.1162/rest.89.3.416*.

Schoellman, T. (2011). Education Quality and Development Accounting. *The Review of Economic Studies*, 79(1):388–417.

Simonovska, I. and Waugh, M. E. (2014). The elasticity of trade: Estimates and evidence. *Journal of International Economics*, 92(1):34–50.

Soderbery, A. (2015). Estimating import supply and demand elasticities: Analysis and implications. *Journal of International Economics*, 96(1):1–17.

Tinbergen, J. (1962). Shaping the World Economy; Suggestions for an International Economic Policy. *Books (Jan Tinbergen)*.

Trefler, D. (1993). International Factor Price Differences: Leontief was Right! *Journal of Political Economy*, 101(6):961–987.

A Estimating the relative price of skilled services

A.1 Theoretical derivation of gravity equation

In this section, I show how my gravity specification can be derived from theoretical trade models. I first derive the specification from an Armington style trade model, and then from an Eaton and Kortum style trade model.

A.1.1 Armington model

There are K industries and I countries, indexed i for source countries and j for destination countries. Each country admits a representative household with preferences

$$U_j = \left(\sum_{i=1}^{I} \sum_{k=1}^{K} (a_j^k)^{1/\sigma} (q_{i,j}^k)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \qquad j = 1, \ldots, I;\ \sigma > 1 \tag{13}$$

where $q_{i,j}^k$ are goods from industry k produced in country i and consumed in country j, σ captures the elasticity of substitution between different varieties, and a_j^k is a country-specific taste term. The taste term is a reduced form way of capturing differences in tastes across countries, including potential non-homotheticicities in preferences. The representative consumer maximizes (13) subject to a constraint

$$\sum_{i=1}^{I} \sum_{k=1}^{K} P_{i,j}^k q_{i,j}^k \leq Y_j$$

where $P_{i,j}^k$ is the price of good k produced in country i and bought in country j. Y_j is income in country j.

Each variety is produced using a constant returns to scale production function with the unit cost function

$$c_i^k = C^k \left(r_{i,1}, \ldots, r_{i,F} \right) \tag{14}$$

where $r_{i,f}$ is the price of factor service f in country i.

Trade costs take an iceberg form and to consume one unit of a good from country i, a country j consumer has to buy $d_{i,j} \geq 1$ goods from country i. The cost term $d_{i,j}$ satisfies

$$\begin{aligned} d_{i,j} &\geq 1 \\ d_{i,i} &= 1 \quad \forall i = 1, \ldots, I \\ d_{i,j} d_{j,l} &\geq d_{i,l}. \end{aligned}$$

Output markets are competitive, which implies that prices satisfy

$$P_{i,j}^k = c_i^k d_{i,j}. \tag{15}$$

Each country has a supply of factor service flows

$$e_{j,f} \geq 0 \quad i = 1, \ldots, I;\ f = 1, \ldots, F,$$

and country income is given by

$$Y_j = \sum_{f=1}^{F} r_{j,f} e_{j,f} \tag{16}$$

An equilibrium is a set of consumption quantities $q_{i,j}^k$, production quantities Q_i^k, factor service prices $r_{i,f}$, unit costs c_i^k, output prices $P_{i,j}^k$, and incomes Y_j such that:

1. $\{q_{i,j}^k\}$ solves the consumer problem given output prices and incomes.
2. Output market clears
$$Q_i^k = \sum_{j=1}^{I} q_{i,j}^k d_{i,j} \forall i, k$$
3. c_i^k and $P_{i,j}^k$ satisfy (14) and (15) respectively
4. Income is given by (16)
5. Factor markets clear
$$e_{i,f} \quad = \quad \sum_k Q_i^k \frac{\partial c_i^k}{\partial r_{i,f}}$$

I will not solve the complete equilibrium, but will only solve for the regression specification relating industry export values to unit costs. In the data, export values between i and j in industry k are presented excluding trade costs (FOB). This corresponds to $P_{i,i}^k q_{i,j}^k$, i.e. the domestic price in i of good k produced in i. Using the competitive output market assumption, this quantity is $c_i^k q_{i,j}^k$.

Consumer optimization implies that for any country-industry pairs (i,k), (i',k')

$$\begin{aligned} \frac{(a_j^k)^{1/\sigma}(q_{i,j}^k)^{-1/\sigma}}{(a_j^{k'})^{1/\sigma}(q_{i',j}^{k'})^{-1/\sigma}} &= \frac{P_{i,j}^k}{P_{i',j}^{k'}} \\ \sum_{i=1}^{I}\sum_{k=1}^{K} q_{i,j}^k P_{i,j}^k = Y_j \end{aligned}$$

Re-arranging the terms gives us

$$P_{i,i}^k q_{i,j}^k = Y_j \frac{a_j^k (P_{i,j}^k)^{1-\sigma}}{\sum_{j',k'} a_j^{k'} (P_{i,j'}^{k'})^{1-\sigma}} \frac{P_{i,i}^k}{P_{i,j}^k}.$$

Taking logarithms, writing total exports $x_{i,j}^k = P_{i,i}^k q_{i,j}^k$, and substituting in (14) for prices gives me

$$\log(x_{i,j}^k) = \delta_{i,j} + \mu_j^k - (\sigma - 1)\log(c_i^k) \tag{17}$$

where

$$\begin{aligned}
\delta_{i,j} &= \log(Y_j) - \log\left(\sum_{i',k'} a_j^{k'} (c_{i'}^{k'} d_{i',j})^{1-\sigma}\right) - \log(d_{i,j}) \\
\mu_j^k &= \log(a_j^k).
\end{aligned}$$

Here, $\delta_{i,j}$ captures all terms that only depend on the bilateral relationship: the income of the buying country, the market access term of the buying country, and all bilateral trading costs between the two countries. μ_j^k captures industry-specific demand effects in the buying country.

A.1.2 Eaton and Kortum model

To derive an industry based gravity equation using an Eaton and Kortum framework, I construct a model close to Chor (2010), who analyzed industry-level trade in an Eaton and Kortum setup. There are I countries where i is an index for a source country and j is an index for a destination country. The model has K goods which are produced domestically, and the production of each good k uses a range of internationally traded intermediate good varieties.

Each country has a representative consumer with preferences

$$U_j = \left(\sum_{k=1}^K a_j^k (Q_j^k)^{\frac{\xi-1}{\xi}}\right)^{\frac{\xi}{\xi-1}} \quad \xi > 1.$$

Each final good k is a composite of internationally traded varieties $q_i^k(z)$ with $m \in [0,1]$. The price of final good k in country i is

$$P_j^k = \left(\int_0^1 p_j^k(m)^{1-\eta} dm\right)^{\frac{1}{1-\eta}}, \quad \eta > \xi > 1,$$

where $p_j^k(m)$ is the country j price of variety m in industry k. The assumption on the elasticity of substitution means that different varieties are more substitutable than goods from different industries.

As varieties are internationally traded, the price $p_j^k(m)$ paid for a variety will reflect the cheapest available variety for country j. When I specify the cost function for varieties, I am therefore interested in the unit cost of *offered* varieties from country i to country j, which I write $p_{i,j}^k(m)$. The price $p_j^k(m)$ is obtained by minimizing over potential source countries i.

The offered price $p_{i,j}^k(m)$ will depend on a deterministic component of costs in country i and industry k, on trade costs between country i and j, and on a stochastic productivity shock to this particular variety. The deterministic component of costs is

$$c_i^k = C^k(r_{i,1}, \ldots, r_{i,F}) \tag{18}$$

where $r_{i,f}$ denotes the factor service price of factor f in country i. Trade costs take an iceberg form and to obtain one unit of an intermediate good from country i, a country j producer has to buy $d_{i,j} \geq 1$ intermediate goods from country i. The cost term $d_{i,j}$ satisfies

$$\begin{aligned} d_{i,j} &\geq 1 \\ d_{i,i} &= 1 \quad \forall i = 1, \ldots, I \\ d_{i,j} d_{j,l} &\geq d_{i,l}. \end{aligned}$$

The offered price is

$$p_{i,j}^k(m) = \frac{c_i^k d_{i,j}}{z_i^k(m)} \tag{19}$$

where $z_i^k(m) \sim Frechet(\theta)$ is a country-industry-variety specific productivity shock which is Frechét distributed with a parameter θ. A random variable Z is Frechét-distributed with parameter θ if

$$P(Z \leq z) = e^{-z^{-\theta}}.$$

I will not solve a full equilibrium for this model, but only derive the gravity trade equation that results from the model. For each variety m in industry k, country j obtains an offer $p_{i,j}^k(m)$ from each country i given by equation (19). The probability distribution of this offer is

$$\begin{aligned} P(p_{i,j}^k(m) \leq p) &= P\left(\frac{c_i^k d_{i,j}}{p} \leq z_i^k(m)\right) \\ &= 1 - e^{-\left(\frac{c_i^k d_{i,j}}{p}\right)^{-\theta}} \\ &= 1 - e^{-\left(c_i^k d_{i,j}\right)^{-\theta} p^\theta} \end{aligned}$$

The best price $p_i^k(m)$ for country i is the minimum of all offers $\min_i p_{i,j}^k(m)$ and has distribution

$$\begin{aligned} G(p) &= P\left(\min_i p_{i,j}^k(m) \leq p\right) \\ &= 1 - P(\max_i p_{i,j}^k(m) > p) \\ &= 1 - \prod_i P(p_{i,j}^k(m) > p) \\ &= 1 - \prod_i (1 - P(p_{i,j}^k(m) \leq p) \\ &= 1 - e^{-\sum_i (c_i^k d_{i,j})^{-\theta} p^\theta} \end{aligned}$$

I write

$$\Phi_j^k = \sum_i \left(c_i^k d_{i,j}\right)^{-\theta}. \tag{20}$$

This expression summarizes country j's access to industry k. It is decreasing in production costs in industry k and in the bilateral trading costs $d_{i,j}$.

Country j chooses to buy a variety from the country with the lowest price. The probability that country i offers the lowest price is

$$\begin{aligned} \pi_{i,j}^k &\equiv P(p_{i,j}^k(z) \leq \min_i p_{i,j}^k(z)) \\ &= \frac{(c_i^k d_{i,j})^{-\theta}}{\Phi_j^k}. \end{aligned}$$

If x_j^k is the total amount of intermediate inputs bought by country j in industry k, the trade flow matrix is

$$x_{i,j}^k = \pi_{i,j}^k x_j^k = \frac{(c_i^k d_{i,j})^{-\theta}}{\Phi_j^k} x_j^k \tag{21}$$

Equation (21) requires that the share of import value coming from country i only depends on the share of inputs for which i is the supplier. This property holds as the Frechet distribution has a desirable property called max-stability, which ensures that the best offered price $p_{i,k}(z)$ to country i is independent of the source of the best offer (see Eaton and Kortum (2002) for a derivation in this particular case, and Mattsson et al. (2014) for a more general discussion of this property of random variables) . This means that the total expenditure on imports from one country will be fully determined by the share of varieties $\pi_{n,i}^k$ bought from that country. The reason is that all countries offer identical distributions of variety prices conditioned on them offering the best prices.

Taking the logarithm of both sides of equation (21) gives me

$$\log(x_{i,j}^k) = \delta_{i,j} + \mu_j^k - \theta \log(c_i^k)$$

where $\delta_{i,j} = -\theta \log(d_{i,j})$ and $\mu_j^k = \log(X_j^k) - \log(\Phi_j^k)$. Thus, the model implies a gravity equation of the right form. Note that when using Eaton and Kortum elasticity estimates θ, there needs to be added a 1 to convert them to the corresponding Armington elasticity estimates σ.

A.2 Results for other factors than skilled labor

In Section 2, I estimated regression (5) to obtain estimates of relative factor service prices across countries. My main interest was in the relative price of skilled services, as this relative price is used directly in development accounting. However, my estimation procedure also yields relative factor service price estimates for capital, intermediate inputs, and energy. Even though I do not use these directly in my development accounting exercising, they are useful to check the plausibility of my factor service price estimation method.

In particular, as capital, intermediate inputs, and energy are partly tradable, we should expect the relative price of these factors compared to unskilled labor to fall with GDP per worker. The reason is that tradable services should have similar prices across countries, whereas we expect the price of unskilled labor services to rise with GDP per worker.

It is possible to quantify how much unskilled service prices should fall with GDP. If we assume that the labor share of output is constant at $1 - \alpha$, the unskilled wage satisfies equation

$$\begin{aligned} w_u &= \frac{w_u}{w_u u + w_s s} \times (w_u u + w_s s) \\ &= \frac{1}{u + \frac{w_s}{w_u} s}(1-\alpha)y \end{aligned}$$

where y in the second line denotes output per worker. Using that the price of unskilled labor services is $r_u = w_u / Q_u$ where Q_u is the quality of unskilled workers, I obtain

$$\log(r_u) = \log(1-\alpha) + \log(y) - \log(h_{trad})$$

where $\log(h_{trad}) = \log(Q_u) + \log(u + \frac{w_s}{w_u} s)$ is human capital according to traditional development accounting methods, as defined in equation (10). Letting r_t be the price of any tradable input service, its relative price compared to unskilled labor services will be

$$\log\left(\frac{r_t}{r_u}\right) = \log(r_t) - \log(1-\alpha) - \log(y) + \log(h_{trad}).$$

If $\log(r_t)$ is constant across countries, we can make the following observation: constant $\log(h_{trad})$ across countries implies that relative tradable factor prices decrease one-to-one with GDP per capita. If $\log(h_{trad})$ is positively correlated with GDP, relative tradable factor service prices will fall slower than one-for-one. And even though it is not explicitly modeled in the equation, we can also note that a non-tradable component of t will also make the relative price/GDP-slope less

Figure 10: Log relative capital services prices and log GDP per worker

negative.

In my data, $\log(h_{trad})$ increases at approximately $0.15 - 0.2$ with GDP per capita. Thus, if capital, intermediate inputs, and energy services are fully tradable, they should have a negative slope of between 0.8 and 0.85 with respect to GDP per worker. If they are not fully tradable, the negative relationship should be weaker. The results are presented in Figures 10-12. The negative relationship between capital and intermediate input service prices and log GDP per worker is similar at -0.6, which is close to what is predicted by my previous reasoning. The conclusions are less stable for energy prices. Here, there is also a negative relationship, but the data is less precise. This is due to energy having a very small factor share in most industries, and the results for energy are more driven by outliers. Reassuringly, large energy producers such as Saudi Arabia, Kuwait, Russia, and Iran have low revealed energy service prices.

A.3 Treatment of intermediate inputs

In my main specification, I include the cost share of intermediate inputs $\alpha^k_{US,int}$. The corresponding estimate $\beta_{i,int}$ identifies $\log\left(\frac{r_{i,int}/r_{i,1}}{r_{US,int}/r_{US,1}}\right)$. This estimate gives the difference between the US and country i in the relative cost of intermediate input and unskilled labor services.

In my interpretation of this parameter, I assume that intermediate inputs are traded. I interpret $r_{i,int}$ as a product of an international price of intermediate inputs r_{int}, which is constant across countries, and a country-specific barrier to international intermediate input markets τ_i, which varies

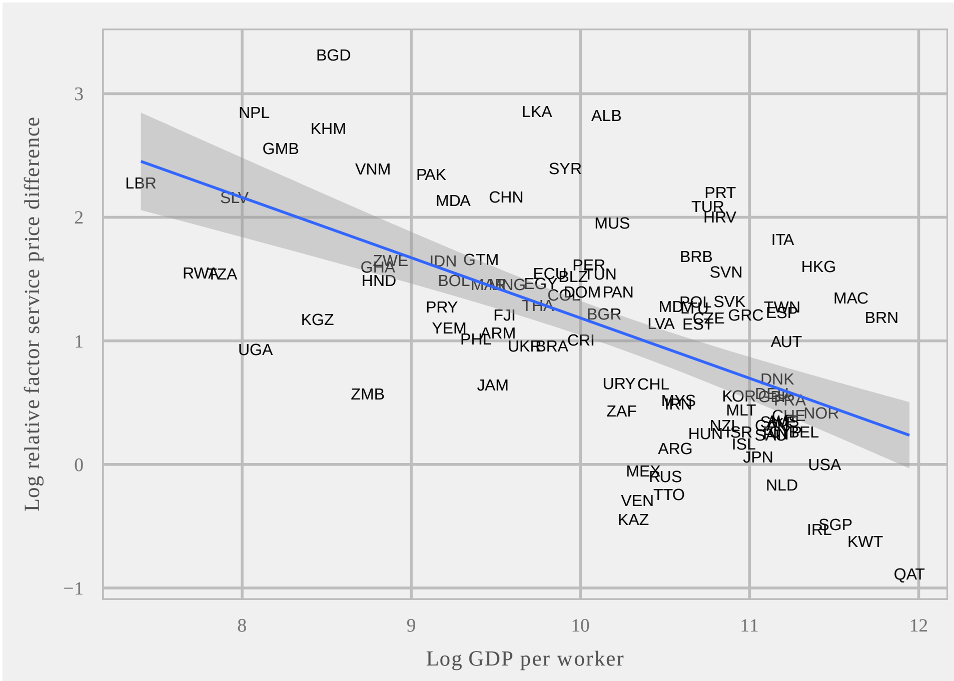


Figure 11: Log relative intermediate input services prices and log GDP per worker

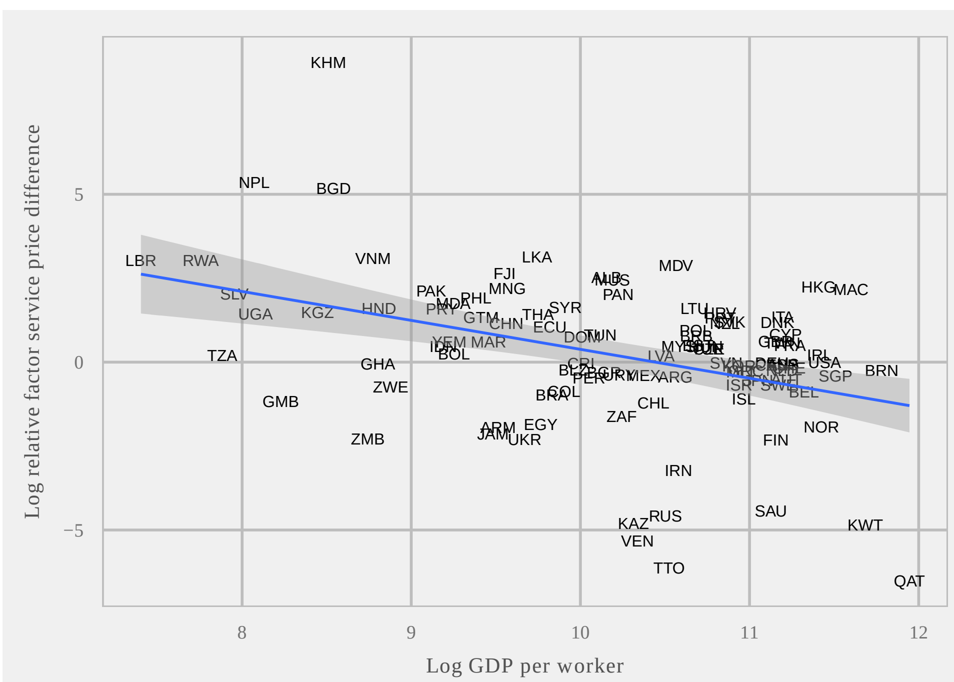


Figure 12: Log relative energy services prices and log GDP per worker

across countries.

With this interpretation,

$$\beta_{i,int} = \log(\tau_i/\tau_{US}) - \log\left(\frac{r_{i,1}}{r_{US,1}}\right).$$

$\beta_{i,int}$ varies across countries for two reasons. First, countries differ in their access to international intermediate goods markets τ_i. Bad access to international markets (high τ_i) gives a high revealed price of intermediate input services (high $\beta_{i,int}$). Second, countries differ in their prices of unskilled labor services $\log\left(\frac{r_{i,1}}{r_{US,1}}\right)$. Countries with a low price of unskilled services have a high revealed price of intermediate input services. This has an intuitive interpretation: relatively inexpensive unskilled labor services make internationally traded intermediate inputs relatively expensive.

If intermediate inputs are not traded and the aim is to identify factor service price differences, a different approach is called for. In this case, there is an indirect effect of factor service price differences via input prices. To reflect this, the intermediate input share in an industry k should be resolved into contributions from different factor services, using the input-output structure to determine the factor shares of industry k's intermediate inputs.

To check the robustness of my baseline specification, I develop an approach that allows for both traded and non-traded intermediate inputs. To implement my approach, I use the US input-output table and assume that services are non-traded and that other goods are traded.[22] I use the EU-KLEMS data together with Occupational Employment Survey data to obtain factor shares in service sectors.

I write N_T for the number of traded goods and N_{NT} for the number of non-traded goods. The input-output table $L$is an $(N_T + N_{NT}) \times (N_T + N_{NT})$ matrix. For each good $k = 1, \dots, N_T + N_{NT}$, I measure its factor shares including its intermediate input share, and I use these measured factor shares to define the *first-stage* factor shares $\tilde{\alpha}_f^k$. This is the same as normal factor shares with one difference. For intermediate inputs, we define $\tilde{\alpha}_f^k$ as the share of inputs that come from non-tradeable intermediates. In the first stage, I am interested in the cost shares of different factors and of tradable inputs. For each industry, $1 - \sum_{f=1}^{F} \tilde{\alpha}_f^k$ gives the share of costs in industry k going to nontraded factor inputs. These first-stage factor shares are the building blocks of the factor shares α_f^k that will be obtained by resolving the cost share of nontraded intermediate inputs into conventional factors and tradable inputs.

I find the factor shares α_f^k of tradable goods recursively by first finding the factor shares of nontradable goods. I define two matrices L_T and L_{NT} where L_T is an $N_T \times N_{NT}$ matrix giving the input uses of nontraded intermediate inputs in the traded sector, and L_{NT} is an $N_{NT} \times N_{NT}$

[22] There is moderate trade in some services such as entertainment, financial services, and transportation, but the distinction captures the large differences in traded shares between services and other goods in the US input-output table.

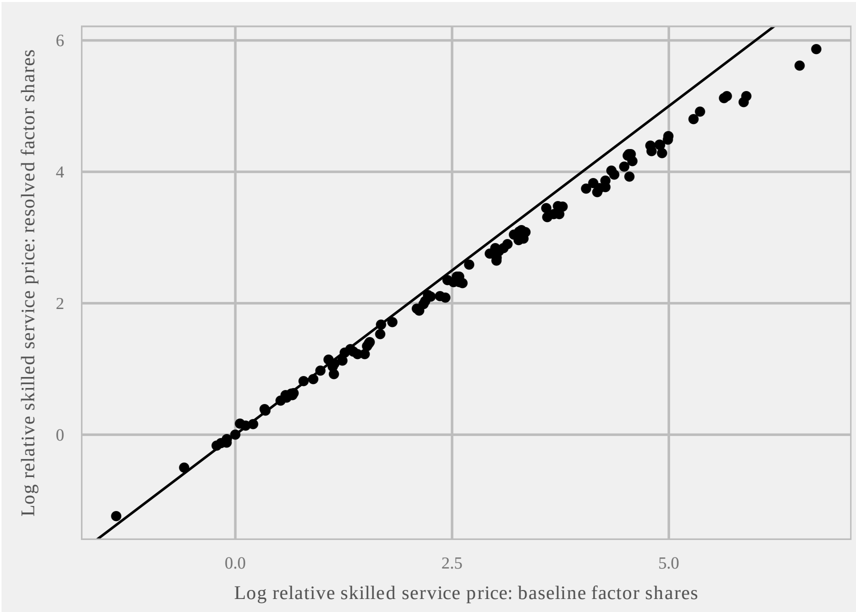


Figure 13: Comparison of estimated relative skilled service prices with different input measurements

matrix giving the cost shares from nontraded inputs in the nontraded sector.

I solve the system recursively. The factor shares of nontraded goods are

$$\alpha_{NT} = \tilde{\alpha}_{NT} + (L_{NT})\alpha_{NT} \Longleftrightarrow \alpha_{NT} = (I - L_{NT})^{-1}\tilde{\alpha}_{NT}$$

where α_{NT} is an $N_{NT} \times F$ matrix, $\tilde{\alpha}_{NT}$ is an $N_{NT} \times F$ matrix, and L_{NT} is an $N_{NT} \times N_{NT}$ matrix. The final matrix α_{NT} gives the factor shares of nontraded services in terms of standard factor shares and traded input shares. All nontraded input shares have been resolved into these constituent parts. Having solved for the factor shares of nontraded goods, the factor shares of traded goods are

$$\alpha_T = \tilde{\alpha}_T + (L_T)\alpha_{NT}.$$

Using this modified definition of factor shares, I can re-estimate my baseline specification. In Figure 13, I compare the estimates for the estimated skilled service coefficient to my baseline estimation. The new results are very similar to my baseline estimates. The reason is that even though resolving the nontraded factors increases the skilled share in all industries (as I move the skilled component of inputs from the intermediate input share to the skill share), the resolving of nontraded factors does little to alter the *relative* skill shares across industries, which are the bases of my estimation.

B Environment

B.1 Heterogeneous skill type aggregator interpretation of Q_u and Q_s

Here, I show that my estimation of the relative quality Q_s/Q_u is consistent with a nested structure where the quality terms Q_u and Q_s arise from aggregation of heterogeneous unskilled and skilled services.

My human capital aggregator is

$$h = \left((Q_u u)^{\frac{\eta-1}{\eta}} + a_s (Q_s s)^{\frac{\eta-1}{\eta}}\right)^{\frac{\eta}{\eta-1}}.$$

Before proving the result, I will provide a formal statement of what equivalence means in this context. Assume that the true human capital aggregator is

$$h = \left((H^u)^{\frac{\eta-1}{\eta}} + a_s (H^s)^{\frac{\eta-1}{\eta}}\right)^{\frac{\eta}{\eta-1}},$$

where H^u and H^s are arbitrary constant returns to scale aggregators of heterogeneous unskilled and skilled services. I say that my relative quality estimation is consistent with an aggregator interpretation if the following holds. Given the definition of quality

$$\begin{aligned} Q_u &\equiv \frac{H^s}{s} \\ Q_s &\equiv \frac{H^u}{u}, \end{aligned}$$

the relative quality of skilled and unskilled labor Q_s/Q_u satisfies the equation

$$\frac{w_s}{w_u} = \frac{Q_s}{Q_u}\frac{r_s}{r_u}, \tag{22}$$

where $\frac{w_s}{w_u}$ is the relative average wage of skilled and unskilled workers, and $\frac{r_s}{r_u}$ satisfies

$$\frac{r_s}{r_u} = a_s \left(\frac{H^s}{H^u}\right)^{-1/\eta}.$$

This quality definition defines the quality of unskilled and skilled labor as the average amount of services provided by each worker in each skill category.

I will now prove the equivalence result. I assume that there are $N_u \geq 1$ types of unskilled labor services and $N_s \geq 1$ types of skilled labor services. A share u_{t_u} of the workforce performs unskilled services of type t_u where $t_u = 1, \ldots, N_u$, and a share s_{t_s} of the workforce performs skilled services of type t_s where $t_s = 1, \ldots, N_s$. The average quality of an unskilled worker of type t_u is Q_{u,t_u} and the average quality of a skilled worker of type t_s is Q_{s,t_s}. The workforce shares sum to the aggregate share of skilled and unskilled workers

$$\begin{aligned}\sum_{t_u=1}^{N_u} u_{t_u} &= u \\ \sum_{t_s=1}^{N_s} s_{t_s} &= s.\end{aligned}$$

With this formulation, the quality of unskilled and skilled labor is defined as

$$\begin{aligned}Q_u &\equiv \frac{H^u(Q_{u,1}u_1,\ldots,Q_{u,N_u}u_{N_u})}{u} = H^u\left(Q_{u,1}\tilde{u}_1,\ldots,Q_{u,N_u}\tilde{u}_{N_u}\right) \\ Q_s &\equiv \frac{H^s(Q_{s,1}s_1,\ldots,Q_{s,N_u}s_{N_u})}{s} = H^s\left(Q_{s,1}\tilde{s}_1,\ldots,Q_{s,N_s}\tilde{s}_{N_s}\right),\end{aligned}$$

where a tilde ($\sim$) denotes that we normalize the unskilled and skilled worker shares u_{t_u} and s_{t_s} with the total supply of unskilled and skilled workers s and u.

Now consider an arbitrary unskilled service type t_u and an arbitrary skilled service type t_s. Assuming that the labor market is competitive, these two types of workers have a relative wage

$$\frac{w_{s,t_s}}{w_{u,t_u}} = \left(\frac{H^s}{H^u}\right)^{-1/\eta}\frac{H^s_{t_s}Q_{s,t_s}}{H^u_{t_u}Q_{u,t_u}} = \frac{r_s}{r_u}\frac{H^s_{t_s}Q_{s,t_s}}{H^u_{t_u}Q_{u,t_u}},$$

where H^s_t and H^u_t denote the partial derivatives of the human capital aggregator functions with respect to their t^{th} elements. The relative wage is a product of i) the relative marginal product of the two aggregators, and ii) the relative marginal contributions of the two skill types to their respective aggregators.

I can use this equation to prove that (22) holds. First, I multiply both sides with $\tilde{s}_{t_s}$ and sum over $t_s = 1,\ldots,N_s$ to obtain

$$\frac{w_s}{w_{u,t_u}} = \frac{r_s}{r_u}\frac{Q^s}{H^u_{t_u}Q_{u,t_u}} \tag{23}$$

where I use Euler's theorem to obtain

$$Q^s = \sum_{t_s=1}^{N_s} Q_{s,t_s}\tilde{s}_{t_s}H^s_{t_s},$$

and use that average skilled wages are defined by

$$w_s = \sum_{t_s=1}^{N_s}\tilde{s}_{t_s}w_s.$$

I obtain equation (22) by applying the same procedure to unskilled labor. I start with equation

(23), invert the equation, multiply both sides with $\tilde{u}_{t_u}$, sum over $t_u = 1, \ldots, N_u$, and finally, I re-invert the equation.

This proves that an aggregator interpretation of the quality terms is equivalent to a two labor type interpretation when estimating the relative quality of skilled labor Q_s/Q_u. When doing development accounting, I make one further restriction in assuming that the unskilled aggregator is a linear aggregator. This allows me to estimate Q_u from Mincerian return data, and together with my estimation of Q_s/Q_u, I can complete the development accounting exercise.

B.2 Supply-side aggregation with multiple industries and trade

I express output with an aggregate production function

$$Y = K^{\alpha}(ALh)^{1-\alpha}.$$

When estimating the aggregate production function, I assume that the economy consists of multiple industries and that it trades with the outside world. In light of this, the aggregate production function should be interpreted as reflecting substitution possibilities within and between industries, as well as substitution possibilities between domestic and foreign production. Here, I discuss the assumptions needed to have a constant returns to scale aggregate production function with multiple industries and trade. In Appendix B.3, I motivate my particular choice of functional form.

I show that a CRS aggregate production function exists under fairly general conditions when countries are price takers in the world market. However, there are more stringent conditions for the existence of a CRS aggregator in variety-based trade models such as Eaton and Kortum and Armington models. In these models, being small compared to the rest of the world is not sufficient to make a country a price-taker, as every country is a large producer of its own varieties. This means that the terms of trade move against countries as they expand factor supplies. Given that my estimation exercise relies on variety models, this is a potential problem.

However, I show that a CRS aggregate production function is possible under a reasonable modification of variety models. The modification is to assume that quality in an Armington model (and absolute productivity advantage in an Eaton and Kortum style model) is homogenous of degree one in aggregate or industry factor supplies. I demonstrate how this modification yields a CRS representation in an Armington model with many small countries, and a similar mechanism applies to the Eaton and Kortum framework.

To motivate my modification, I first argue that the terms of trade effect is unlikely to be a long-run phenomenon. In particular, if such a long-run effect existed, terms of trade would be sensitive to subdivisions of countries. For example, if Scotland and UK were formally separated, a long-run terms of trade effect from size would imply that both English and Scottish terms of trade should improve with respect to the rest of the world if they split. This feature is unrealistic, and it suggests that whatever scarce resource makes the global demand curve for a country's goods slope downward – restricted number of varieties in an Armington framework, or restricted idea generation in an Eaton and Kortum framework – this scarce resource should scale with size.[23]

Once I modify the Armington model such that qualities scale with factor supplies, a CRS aggregate production function representation is possible. Furthermore, allowing quality to scale with inputs does not affect the key feature of the model: that relative exports across countries and goods are determined by relative trade costs and relative production costs.

B.2.1 Setup

To study the conditions needed for the existence of a CRS representation, I study a general multi-industry model of a country with K industries and F factor services in an open economy $i \in I$. I use a dual formulation. The production technology in country i for each industry is CRS and represented by the unit cost function $c_i^k(r_{i,1}, \ldots, r_{i,F})$. Factor service supplies are $v_{i,f}$. I write y_i^k for production in industry k and x_i^k for consumption in industry k (these two quantities might differ due to trade). I write p_i^k for the domestic price of good k. There exists a representative consumer whose preferences are defined by an expenditure function $e(\mathbf{p}_i, u_i)$. I assume that these preferences are homothetic, which means that there exists a utility representation of preferences such that the expenditure function can be written

$$e(\mathbf{p}_i, u_i) = \tilde{e}(\mathbf{p}_i)u_i$$

for some function $\tilde{e}$. Throughout this section, I assume that preferences are homothetic and I will write $\tilde{e}$ without a tilde going forward.

A CRS aggregator representation exists if prices are unchanged and output and consumption scale linearly when we scale factor inputs. Formally, I say that a CRS aggregator representation exists if the following condition holds. Let $x_i^k, y_i^k, u_i, r_{i,f}, p_i^k, c_i^k$ be an arbitrary equilibrium given factor supplies $v_{i,f}$. A CRS representation exists if for each such equilibrium, a factor supply $\lambda v_{i,f}$ implies that $\lambda x_i^k, \lambda y_i^k, \lambda u_i, r_{i,f}, p_i^k, c_i^k$ is an equilibrium.

I first consider a model where each country is a price-taker in the world market. In this case,

[23] This modification is related to Krugman (1988) who shows that growing countries do not face **deteriorating** terms of trade, and he explains this with a variety model of growth. For a contrasting perspective, see Acemoglu and Ventura (2002) who argue that a country's terms of trade deteriorates when it grows through capital accumulation.

the equilibrium conditions can be written as:

$$\begin{aligned}
\sum_{k=1}^{K} \frac{\partial c_i^k}{\partial r_{i,f}} y_i^k &= v_{i,f} \quad f = 1, \ldots, F \\
\frac{\partial e}{\partial p_i^k} u_i &= x_i^k \quad k = 1, \ldots, K \\
c_i^k &\geq p_i^k \quad = 0 \text{ if } y_i^k > 0 \\
e(\mathbf{p}_i) u_i &= \sum_{f=1}^{F} r_{i,f} v_{i,f}
\end{aligned}$$

The first equation gives clearing conditions for the factor markets, where the left-hand side uses Shepherd's lemma applied to the unit cost function to derive factor demands for each factor f and for industry k. The second equation expresses consumer demand, applying Shepherd's lemma to the expenditure function. The third equation is a zero-profit condition, where the inequality constraint reflects that I allow for zero production. The fourth equation is the budget constraint for the representative consumer.

By inspection, this system of equations allows for a CRS aggregator representation. If there exists a set of prices such that $y_i^k, x_i^k, u_i, v_{i,f}$ solve the system, then any scaling $\lambda y_i^k, \lambda x_i^k, \lambda u_i, \lambda v_{i,f}$ for $\lambda > 0$ solves the system for the same set of prices.

To study the Armington case, I retain the assumption that the country is small in the aggregate world economy. However, the country is large in its own varieties. I represent this with an Armington model with a continuum of countries and K goods. I write $i \in [0, 1]$ for the country on which I focus.

There are K final goods. Each final good is assembled domestically using a composite of country-industry specific intermediate varieties that are traded between countries. To produce good k, one needs an input variety from each country in the world. I assume that there are no trade costs so that the unit cost C_i^k of assembling final good k in country i is the same in every country and equal to

$$C_i^k \equiv C^k = \left(\int_0^1 a_j^k (c_j^k)^{1-\sigma} dj \right)^{\frac{1}{1-\sigma}} \qquad \sigma > 1.$$

I normalize a_j^k so that the unit production costs are $c_j^k = 1$ for all countries $j \neq i$ (our unit of analysis). This means that

$$C^k = 1 \quad k = 1, \ldots, K.$$

Write $q_{i,j}^k$ for the amount of input to industry k that is produced in country i for use in country j. As there are no trading costs and countries are symmetric, $q_{i,j}^k$ does not depend on destination j.

Furthermore, using Shepherd's lemma,

$$q_{i,j}^k = \frac{\partial C^k}{\partial c_i^k} x_j^k,$$

where x_j^k is the country j consumption of final goods in industry k.

I can now write down the equilibrium definition.

$$\begin{aligned}
q_{i,j}^k &= a_i^k (c_i^k)^{-\sigma} x_j^k \\
p_{i,k} &= c_{i,k} \\
x_i^k &= \frac{\partial e(1,\ldots,1)}{\partial P^k} u_i \\
\sum_{f=1}^{F} r_{i,f} v_{i,f} &= e(1,\ldots,1) u_i \\
\sum_{k=1}^{K} \int_0^1 q_{i,j}^k \frac{\partial c_i^k}{\partial r_{i,f}} &= v_{i,f}
\end{aligned}$$

The first equation gives country j's demand for industry k goods produced in country i. The formulation uses that the price index $P_j^k = C_j^k = 1$ for all j. The second equation is a non-profit condition for production in country i. There is no inequality constraint, reflecting that with a CES specification of production technology from intermediates, production of each variety is always positive. The third equation applies Shepherd's lemma to the consumer's expenditure function. It is evaluated at $(1,\ldots,1)$ as all prices $P^k = 1$. The fourth and fifth equations give the consumer budget constraints and the factor market clearing condition.

By inspection, there does not exist a CRS aggregator representation of this system. In the first equation, we see that scaling output will change prices, violating the assumption that there exist scaled equilibria with the same prices. This reflects a terms of trade effect whereby scaling output depresses the terms of trade.

However, there exists a simple modification of the system to obtain a CRS aggregator. If I define $a_i^k = \Phi_i^k(v_{i,1}^k, \ldots, v_{i,F}^k)$ for some CRS aggregator Φ_i^k, there exists a CRS representation of the equilibrium. Allowing the quality term a_i^k to scale linearly with factor supply captures the intuition that subdivision of observation units should not affect trade patterns with third parties. Even with this modification, *relative* trade patterns across industries are still shaped by *relative* costs, and if we were to add trade costs, then trade costs would affect the distribution between domestic uses and exports, and trade costs would also affect relative exports to different countries.

B.3 Functional form of aggregate production function

My aggregate production function has the form

$$Y = K^{\alpha}(ALh)^{1-\alpha}.$$

As discussed in Appendix B.2, this represents an aggregation taking into account the existence of multiple industries and opportunities for international trade. In this section, I discuss my choice of functional form.

I choose a Cobb-Douglas aggregator between capital and labor services. This is standard in the development accounting literature, and can be motivated by there being constant labor shares across countries (Gollin, 2002).[24]

For the human capital aggregator, I use a CES aggregator of skilled and unskilled labor services, which is standard in the labor economics literature (Acemoglu and Autor, 2011). Ideally, I should have a skill aggregator that was formally aggregated from production functions on the industry level together with a trade model. Unfortunately, there is no straightforward aggregation to a CES representation from industries with heterogeneous factor shares. Thus, the constant elasticity assumption should be interpreted as an approximation to a more freely specified underlying aggregator.

One way of testing my assumption of constant elasticity of substitution is by plotting the cross-country relationship between log relative factor service prices and log relative factor supplies. Theoretically, these should be related by

$$\log\left(\frac{r_s}{r_u}\right) = \log(a_s) - \frac{1}{\eta}\log\left(\frac{Q_s s}{Q_u u}\right).$$

If the CES assumption is true, the relationship should be linear. The test is not ideal, as my estimated relative quality $\log\left(\frac{Q_s}{Q_u}\right)$ is implicitly present in the relative price of factor services, and thus it appears on both sides of the equation, which biases the relationship towards being linear. However, if the log relative supply of skilled and unskilled workers $\log\left(\frac{s}{u}\right)$ was not linearly related to the relative quality $\log\left(\frac{Q_s}{Q_u}\right)$, the relationship would not be linear. Thus, testing the linearity of this relationship offers an opportunity to falsify the CES assumption. The results are plotted in Figure 14, which suggests that the linearity assumption is appropriate.

Looking ahead, potential extensions include modifying the functional form to allow for capital-skill complementarities and non-unitary elasticity of substitution between labor and capital.

[24] Recent studies cast doubt on the Cobb-Douglas assumption (Oberfield and Raval, 2014), and Caselli (2005) suggests that the elasticity of substitution between capital and labor can be a crucial parameter in development accounting. I do not pursue this line of inquiry further here, but it is an interesting avenue of future research. The Cobb-Douglas specification of labor and capital also precludes capital-labor complementarities.

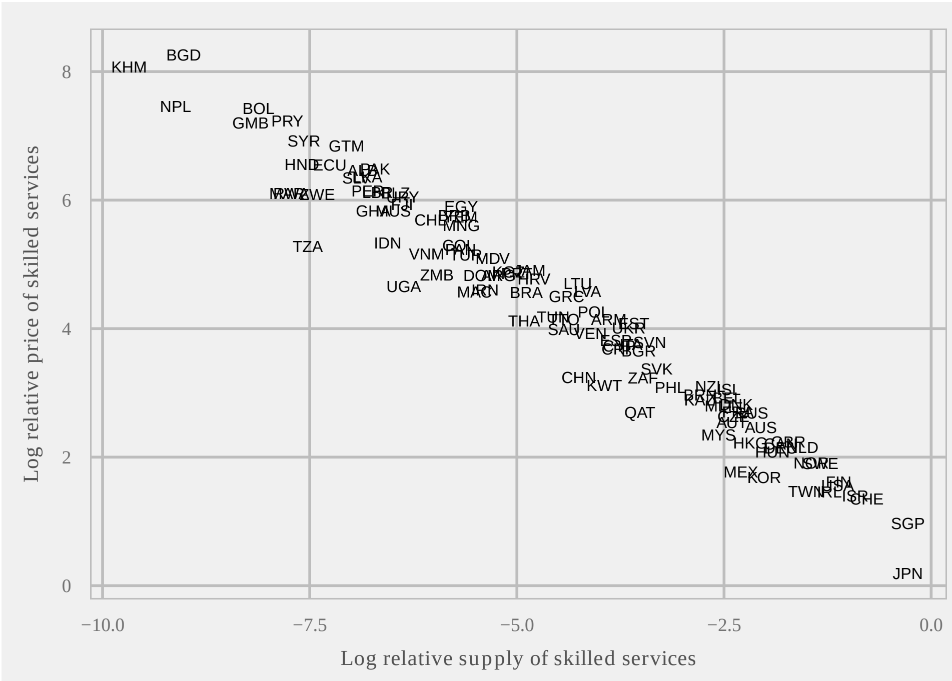


Figure 14: Testing constant elasticity of substitution

C Development accounting

C.1 Occupational vs schooling based skill cutoff

I define the share of unskilled and skilled workers u and s as the shares of people working in an unskilled and skilled occupation, respectively. This contrasts to the approach taken in Caselli and Coleman (2006), B Jones (2014a), and Caselli (2016) who define the share of skilled workers as the share of individuals having an educational attainment above a pre-specified threshold (for example, primary education and above, high school and above, or college and above).

The distinction between the share of workers with a skilled occupation and the share of workers with a certain educational level does not matter if all countries have the same mapping between educational attainment and occupational skill level. However, there is no a priori reason to believe that this mapping should be the same across countries. Acemoglu and Autor (2011) have highlighted the importance of distinguishing between educational attainment and tasks when analyzing US time series data as the allocation of skills to tasks is an equilibrium outcome. Their point is more relevant when analyzing differences between countries with very large differences in educational systems. When educational attainment does not map to occupational skill content in the same way across countries, this modeling choice matters.

I choose an occupational definition for two reasons. First, there are multiple ways of acquiring skills, and education is only one of them. Many people learn skilled occupations outside the educational system, and poor quality of schooling increases the risk that schooling does not fully reflect skill acquisition. When skills are not equal to educational attainment, the complexity of the occupation is a proxy for skill. Indeed, as long as there is a positive skilled wage premium, barring compensating differential concerns, people will work in the most complex occupations that they can perform. Second, occupation is closer to the definitions used for skill shares in my trade data exercise, where I define the skill share as the share of gross output that goes to the payroll of workers in certain occupations.

Thus, I measure the share of skilled workers in line with the ILO's ISCO-08 definitions of skill requirements and major occupational groups. The ILO defines 10 major occupational groups and four skill levels. The occupational groups and their respective skill levels are presented in Figure 15. I use the ILOSTAT database to obtain s as the share of the labor force working as managers, professionals, or technicians and associated technicians, i.e. skill categories 3 and 4 (I define the armed forces as primarily unskilled). I define the unskilled share as $u \equiv 1 - s$.

Figure 16 compares the results from an education based and occupation based definition of the skill share. Figure 16 shows that for poor countries, the share of high school educated workers and the share of skilled workers approximately coincide. For rich countries, there are much more high school educated workers than skilled workers. This is evidence that the mapping between educational attainment and skill level is different in rich and poor countries, and that the educational cutoff for being in a skilled occupation is lower in poor countries.

These results suggest that education based ratios of skilled and unskilled workers will exaggerate rich-poor differences in the relative supply of skilled and unskilled workers. Overall, my method is therefore more conservative when it comes to finding an important role for human capital. I find that this difference matters when I apply the method in B Jones (2014) using my data definitions. He defines a skilled worker as someone having any education above primary education, and finds that even with an elasticity of substitution of 2, human capital is very important in explaining world income differences. With my definition of skilled labor, an elasticity of substitution of 2 means that human capital is only modestly more important than what is found when using traditional development accounting methods.

C.2 Measurement of unskilled labor quality Q_u

I define the quality of unskilled labor Q_u using a Mincerian definition. The quality of unskilled labor is defined as

$$Q_u = \exp(\phi(S_u)).$$

Here, S_u is defined as the average years of schooling of unskilled workers. ϕ is a function capturing the Mincerian returns to education. I use a functional form from Hall and C Jones (1999) and

Figure 15: Mapping of ISCO-08 major groups to skill levels

ISCO-08 major groups	Skill level
1 Managers	3 + 4
2 Professionals	4
3 Technicians and Associate Professionals	3
4 Clerical Support Workers 5 Services and Sales Workers 6 Skilled Agricultural, Forestry and Fishery Workers 7 Craft and Related Trades Workers 8 Plant and Machine Operators, and Assemblers	2
9 Elementary Occupations	1
0 Armed Forces Occupations	1 + 2 + 4

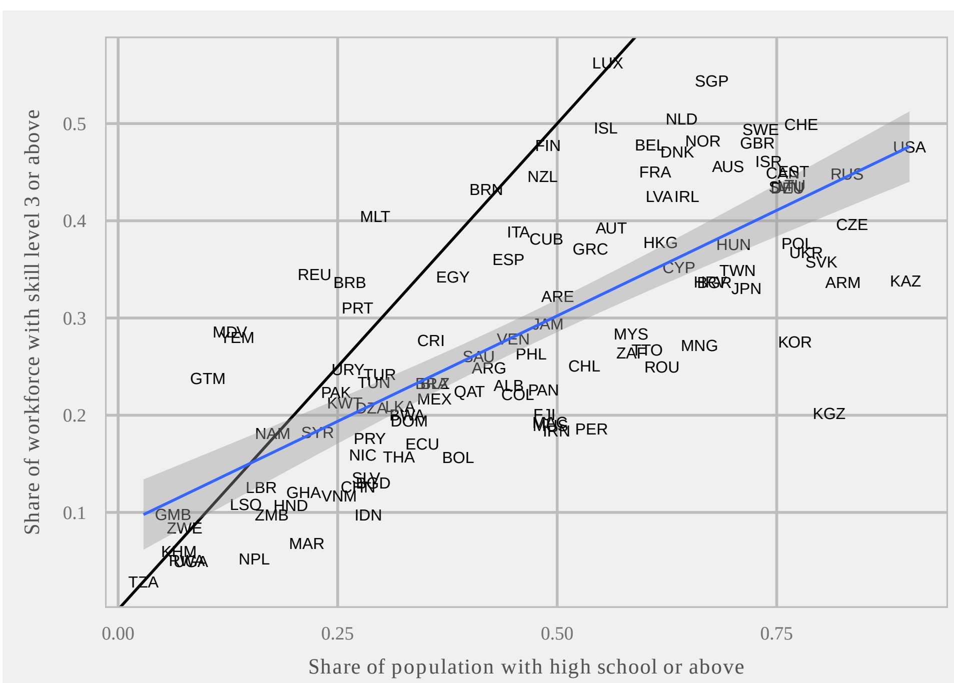


Figure 16: High school and above and share of skilled occupations

Caselli (2005) where $\phi(S)$ is a piecewise linear function with slope 0.13 for $S < 4$, a slope 0.1 for $S \in [4, 8)$, and a slope 0.08 for $S \geq 8$.

I measure S_u by using the data from Barro and Lee (2013). I assume that there is positive sorting between education and skill levels in occupation, and that S_u represents the average years of schooling of the share u of the population working in unskilled occupations. The Barro-Lee data does unfortunately not record the cumulative distribution of years of schooling, but only total schooling attainment within different levels of schooling. It records the number of schooling years at the primary level, the secondary level, and the higher level.

To calculate S_u, I first note that in the vast majority of countries, the cutoff between skilled and unskilled workers goes below the college level, and I attribute none of the schooling years in higher education to unskilled workers. To calculate the years of schooling in primary and secondary school that should be attributed to low skilled workers, I subtract 7 times the share of skilled workers from both primary and secondary school years, using the approximation that all skilled workers have finished high school and that primary and secondary school both are both 7 years. The results are not sensitive to details in this specification. After this subtraction, I divide the remaining primary and secondary school years with the share of unskilled workers to obtain S_u.

C.3 Robustness to industry function specification and endogenous technology bias

My baseline estimates relied on the assumption that it was possible to approximate unit cost differences from the US by log-linearizing around the US cost structure. In terms of assumptions on industry production functions, this assumption amounts to assuming that industry production functions are Cobb-Douglas. Furthermore, to interpret estimates r_s/r_u in terms of human capital, I needed to assume that there were no skill-biased technology differences between countries. This section tests the robustness of my results to deviations from these two assumptions.

The section has three subsections. In Appendix C.3.1, I describe an environment featuring CES industry production functions, and endogenous technology bias in response to relative factor service price variations along the lines of Caselli and Coleman (2006), Acemoglu et al. (2007), and Caselli (2016). In Appendix C.3.2, I show how it is possible to quantify the extent of bias introduced by varying production function assumptions. Appendix C.3.3 describes the results of the quantification exercise.

C.3.1 Environment

I assume that industry cost functions satisfy

$$c_i^k\left(\frac{r_{i,1}}{Z_{i,1}^k},\ldots,\frac{r_{i,F}}{Z_{i,F}^K}\right)=\left(\sum_{f=1}^F a_f^k\left(\frac{r_{i,f}}{Z_{i,f}^k}\right)^{1-\xi}\right)^{\frac{1}{1-\xi}}\qquad \xi>0,$$

where $r_{i,f}$ is the factor service price of factor f in country i, a_f^k is the factor share of factor f in industry k, $\xi > 0$ is the elasticity of substitution, and $Z_{i,f}^k$ is a factor-augmenting technology term.

The technology terms vary endogenously across countries in response to changes in relative factor prices. In modeling this choice, I follow Acemoglu (2007) and assume that there exists a cost function $G^k(Z_{i,1}^k,\ldots,Z_{i,F}^k)$ capturing the cost of acquiring a technology bundle. I assume that G^k is convex and homogenous of degree $\gamma > 1$. A country's technology bundle in an industry is the solution to

$$\tilde{c}_i^k=\min_{\{Z_{i,1}^k,\ldots,Z_{i,F}^k\}}\left\{c\left(\frac{r_{i,1}}{Z_{i,1}^k},\ldots,\frac{r_{i,F}}{Z_{i,F}^k}\right)+\frac{P_i^kG^k(Z_{i,1}^k,\ldots,Z_{i,F}^k)}{\bar{Z}_i}\right\}\tag{24}$$

where $\tilde{c}_i^k$ is the unit cost of good k in country i taking into account technology acquisition costs, $\frac{1}{\bar{Z}_i}$ is a country specific technology diffusion barrier, and P_i^k is the price of good k in country i. In equilibrium, $P_i^k = \tilde{c}_i^k$.

This specification aims at capturing a mechanism highlighted in the literature: the possibility of endogenous technology bias in response to variations in relative factor service prices (Caselli and Coleman, 2006; Acemoglu, 2007; Caselli, 2016). Even though other mechanisms might be active, I have chosen a model specification that allows me to focus on this particular mechanism, and exclude other potential mechanisms. By defining technology choice as minimizing a unit cost, I preclude scale effects as my unit cost specification implies that the cost of acquiring technology scales with total industry production. By assuming that technology acquisition costs in an industry are denominated in industry output (which is implicit by including the price P_i^k), I preclude that technology choices are affected by the relative price of output and technology acquisition. Lastly, I assume that technology barriers $\frac{1}{\bar{Z}_i}$ are common across factors and industries. This precludes that technology choices are affected by industry specific technology diffusion barriers, and it precludes that factor biases in technology arise due to factor specific technology diffusion barriers.

To solve for the technology choice, I take the first-order conditions associated with problem (24).

$$(c_i^k)_f\frac{r_{i,f}}{(Z_{i,f}^k)^2}=\frac{P_i^kG_f^k}{\bar{Z}_i}\qquad f=1,\ldots,F\tag{25}$$

where the subscripts f on c_k^i and G^k denote partial differentiation with respect to argument number f. Multiplying both sides by $Z_{i,f}^k$, summing over f, and using that c_i^k and G^k are homogenous of degree 1 and $\gamma > 1$ respectively, I obtain

$$c_i^k = \frac{\gamma P_i^k G^k}{\bar{Z}_i}.$$

This means that

$$\begin{aligned} P_i^k &= \tilde{c}_i^k \\ &= c_i^k + \frac{P_i^k}{\bar{Z}_i} G^k \\ &= c_i^k \left(1 + \frac{1}{\gamma}\right). \end{aligned}$$

Substituting this back into the first-order condition (25), I obtain

$$\frac{(c_i^k)_f r_{i,f}}{c_i^k Z_{i,f}^k} = \left(1 + \frac{1}{\gamma}\right) \frac{G_f^k Z_{i,f}^k}{\bar{Z}_i}. \tag{26}$$

Noting that the left-hand side is

$$\alpha_{i,f}^k = \frac{(c_i^k)_f r_{i,f}}{c_i^k Z_{i,f}^k},$$

where $\alpha_{i,f}^k$ is the factor share of factor f in industry k for country i, equation (26) captures the intuition that a country expands further in a factor-augmenting technology if it has a high share of its costs devoted to that factor.

I can provide a stronger characterization if I put more structure on G^k and assume that it is given by

$$G^k = \sum_{f=1}^{F} \tilde{a}_f^k (Z_{i,f}^k)^\gamma \quad \gamma > 0.$$

In this case, the factor bias can be expressed as

$$\frac{\alpha_{i,f}^k}{\alpha_{i,1}^k} = \frac{\tilde{a}_f^k}{\tilde{a}_1^k} \left(\frac{Z_{i,f}^k}{Z_{i,1}^k}\right)^\gamma$$

I normalize $\tilde{a}_f^k = \alpha_{US,f}^k$ to ensure that the US has no technological bias. In this case, the relative factor bias is

$$\left(\frac{Z_{i,f}^k}{Z_{i,1}^k}\right) = \left(\frac{\alpha_{i,f}^k / \alpha_{US,f}^k}{\alpha_{i,1}^k / \alpha_{US,1}^k}\right)^{\frac{1}{\gamma}} \tag{27}$$

The relative factor bias is uniquely determined by the relative factor shares compared to the US. The smaller is γ, the more strongly relative factor technologies react to relative factor service prices.

C.3.2 Quantification

In this section, I quantify how my baseline estimation is affected by the modified assumptions on the industry production functions. In particular, I test how well my baseline method estimates relative factor service prices $\log\left(\frac{r_{i,f}/r_{i,1}}{r_{US,f}/r_{US,1}}\right)$ in this new environment.

For this purpose, I solve for the technology choice $Z^k_{i,f}$ and for unit costs c^k_i given factor prices $r_{i,f}$. I then run a regression

$$\log(c^k_i) = \delta_i + \mu^k + \sum_{f=2}^{F} \tilde{\beta}_{i,f}\alpha^k_{US,f} \quad \tilde{\beta}_{US,f} = 0.$$

I am interested in which factor service price combinations $\tilde{r}_{i,f}$ that generate $\tilde{\beta}_{US,f}$ which are similar to the $\beta_{i,f}$ that I find in my baseline estimation (5). By comparing the baseline $\beta_{i,f}$ with $\log\left(\frac{\tilde{r}_{i,f}/\tilde{r}_{i,1}}{\tilde{r}_{US,f}/\tilde{r}_{US,1}}\right)$, I can test how well my baseline estimate $\beta_{i,f}$ captures the relative price of factor services $\log\left(\frac{r_{i,f}/r_{i,1}}{r_{US,f}/r_{US,1}}\right)$ in this new environment. I do not run the full trade regressions, as I only modify how factor prices map to unit costs, and I do not modify how unit costs map to trade flows. I perform the regression on c^k_i excluding technology acquisition costs. As equilibrium technology acquisition costs uniformly scale unit costs, they do not affect the regression.

The detailed implementation of my method is as follows. I assume that there are 84 industries corresponding to the NAICS 4-digit manufacturing industries used in the baseline specification, and that there are two countries: "Poor" and the US. I assume that there are only two countries to reduce the number of parameters to estimate, while still capturing broad differences between rich and poor countries. I normalize US factor prices $r_{US,f} \equiv 1$, and US unskilled technology $Z^k_{US,1} = 1$ for all $k = 1, \ldots, 84$. I set the technology choice parameters to $\tilde{a}^k_f = \alpha^k_{US,f}$ which normalizes US technologies to $Z^k_{US,f} = 1$ for all factors and industries. The normalization of the technology choice function implies a normalization of the unit cost function, which becomes

$$c^k_i = \left(\sum_{f=1}^{F} \alpha^k_{US,f}\left(\frac{r_{i,f}}{Z^k_{i,f}}\right)^{1-\xi}\right)^{\frac{1}{1-\xi}}. \tag{28}$$

Furthermore, as only relative factor service prices are relevant for my estimation exercise, I can without loss of generality normalize $r_{Poor,1} = Z^k_{Poor,1} = \bar{Z}_i = 1$.

My task is to find $\tilde{r}_{Poor,f}$ for $f = 2, \ldots, F$ that replicate my baseline results. First, I use the CES industry production form to derive that

$$\frac{\alpha^k_{Poor,f}}{\alpha^k_{Poor,1}} = \frac{(\tilde{r}_{Poor,f}/Z^k_{Poor,f})^{1-\xi}}{(\tilde{r}_{Poor,1}/Z^k_{Poor,1})^{1-\xi}}\frac{\alpha^k_{US,f}}{\alpha^k_{US,1}}.$$

By combining this expression with equation (27), I obtain

$$\left(\frac{Z^k_{Poor,f}}{Z^k_{Poor,1}}\right) = \left(\frac{\tilde{r}_{Poor,f}/Z^k_{Poor,f}}{\tilde{r}_{Poor,1}/Z^k_{Poor,1}}\right)^{\frac{1-\xi}{\gamma}} \iff \frac{Z^k_{Poor,f}}{Z^k_{Poor,1}} = \left(\frac{\tilde{r}_{Poor,f}}{\tilde{r}_{Poor,1}}\right)^{\frac{1-\xi}{\gamma+1-\xi}}.$$

Thus, for each set of $\tilde{r}_{Poor,f}$, I can solve for technologies $Z^k_{Poor,f}$ and for unit costs c^k_{Poor}. I run the regression

$$\log(c^k_i) = \delta_i + \mu_k + \sum_{f=2}^{F} \tilde{\beta}_{i,f}\alpha^k_{US,f} \qquad \begin{array}{l} \tilde{\beta}_{US,f} = 0 \\ i = Poor, US \\ k = 1, \ldots, 84 \end{array}.$$

I solve for $\tilde{r}_{Poor,f}$ for $f = 2, \ldots, F$ such that $\tilde{\beta}_{Poor,f}$ matches $\beta_{Poor,f}$ from the baseline specification (I define $\beta_{Poor,f}$ by regressing my estimated $\beta_{i,f}$ on log GDP per worker $\log(y_i)$ for each f, and I define $\beta_{Poor,f}$ as the fitted value for $\log(y) = 9$). By comparing $\log\left(\frac{\tilde{r}_{Poor,s}/\tilde{r}_{Poor,1}}{\tilde{r}_{US,f}/\tilde{r}_{US,1}}\right)$ with $\beta_{Poor,s}$, I can gauge how biased my baseline estimation is in estimating the log relative price of skilled services. I test the effect of this bias on my development accounting exercise by redoing the development accounting exercise using an estimate of relative skilled service prices

$$\log\left(\frac{r_{i,s}/r_{i,1}}{r_{US,f}/r_{US,1}}\right) = \left(\frac{\log(y_{US}) - \log(y_i)}{\log(y_{US}) - 9}\right)\log\left(\tilde{r}_{Poor,s}\right).$$

C.3.3 Results

Table 12 shows the share of income differences explained by human capital for different values of the elasticity of substitution ξ and the endogenous technology parameter γ. A large γ means that technology choices are insensitive to variations in relative factor service prices. Unsurprisingly, we see that the endogenous technology choice parameter γ does not matter when $\xi = 1$. In this case, the production function is Cobb-Douglas and all technology differences are neutral. Furthermore, when $\gamma = 5$, the results for different ξ are similar to those found in Table 9 when there were no endogenous technology differences. This reflects that with a large γ, technology choices respond weakly to changes in relative factor service prices.

Overall, there is no monotone effect of endogenous technological change on the importance of human capital. For $\xi = 0.6$ and $\xi = 0.8$, making endogenous technology choices more flexible (smaller γ) makes human capital less important. For $\xi = 1.4$, making technology choices more flexible makes human capital dramatically more important. Overall, no specification reduces the importance of human capital below 50%.

C.4 Intuition

Here, I interpret the findings in Table 12.

Table 12: Share of income differences explained by human capital for different ξ and γ

	$\gamma = 1.01$	$\gamma = 1.1$	$\gamma = 2$	$\gamma = 5$
$\xi = 0.6$	0.55	0.56	0.62	0.65
$\xi = 0.8$	0.61	0.61	0.62	0.63
$\xi = 1$	0.64	0.64	0.64	0.64
$\xi = 1.2$	0.69	0.69	0.69	0.69
$\xi = 1.4$	6.83	6.48	1.01	0.90

To explain the intuition, I illustrate the active mechanisms with an example where there is only US and a poor country, and that there are two factor inputs – skilled and unskilled labor services, and only two industries – one skill intensive and one non-skill intensive industry. Figure **??** illustrates the relationship between relative skilled service prices and relative unit costs in this setting. The higher the relative skilled services prices, the higher the relative unit cost in the skill intensive industry. The slope of the line is the difference in skill shares between the two industries. When I observe a difference in relative unit costs, I can read off from the graph the difference in relative skilled services prices that correspond to an observed difference in relative unit costs.

The constant slope reflects a Cobb-Douglas assumption which that ensures that the poor country's factor share is the same as the US. However, even when factor shares change, it holds that the slope of the curve is the difference in the skilled factor share between the two industries in the poor country. Thus, to analyze how a deviation from the Cobb-Douglas assumption affects my estimates, I can focus on how the deviation changes the difference in factor shares between the two industries.

We can begin by considering the case when there are small deviations from an elasticity of substitution $\xi = 1$ and small deviations in relative service prices. In this case, $\xi > 1$ leads to higher estimated relative price differences across countries, and the converse is true when $\xi < 1$. If skilled and unskilled labor are gross substitutes, higher relative skilled service prices lower the skilled labor share in industry production functions. Locally, this means that the difference in skilled labor share between industries falls, which means that the curve slopes less than $\alpha^{skill}_{US,skill} - \alpha^{nonskill}_{US,skill}$ where I denote industry superscripts $k = skill, unskill$. Larger differences in relative factor service prices are need to rationalize any given difference in relative unit costs. The converse is true for $\xi < 1$.

The conclusion that higher ξ lead to larger estimated price differences for a given estimated unit cost difference holds as unit cost differences grow and the elasticity of substitution gets larger. It is more complicated when ξ becomes smaller and unit cost differences become larger. In this case, the complementarity between skilled and unskilled services and the high relative price of skilled services will drive the factor share of skilled workers toward 1. Then the *difference* in skill shares is very small, and large differences in relative factor service prices are needed to explain differences in relative unit costs.

I can now now analyze the results in Table 12 in light of this reasoning. In Table 9, we see this locally as going to $\xi = 1.2$ increases the importance of human capital, and going to $\xi = 0.8$ decreases the importance of human capital. But we can also see that the global effect is different, and that results are non-monotone. The estimated importance of human capital is larger for $\xi = 0.6$ than for $\xi = 0.8$.

Having considered different ξ without endogenous technology differences, we can now consider the case when there are endogenous technology differences. In Table 12, we see that making technology more flexible makes human capital more important for $\xi = 1.4$ and human capital less important for $\xi = 0.6, 0.8$. I interpret the two cases in turn. For $\xi = 1.4$, skilled and unskilled labor services are gross substitutes. This means that as skilled services become more expensive, the skilled cost share falls. This biases technology away from skilled labor. The result is that the difference between skilled shares in different sectors shrink, as prices and technology bias push down the skill share to zero in all sectors. Large price differences are needed to explain unit cost differences.

The converse is true when $\xi = 0.6, 0.8$. In this case, we saw that without endogenous technological change, differences shrink between sectors as the skill share goes to 1 in all sectors as relative skill prices increase. In this case, endogenous technological change prevents this. A higher skill share increases the bias towards skill augmenting technologies, and this reduces the pace at which the skilled factor share goes to 1. Thus, smaller price differences suffice to explain relative cost differences and the importance of human capital falls.

D Robustness

D.1 Discussion: Industry-dependent trade elasticities

In my estimates, I assume that the elasticity of trade σ is common across industries. A number of papers in the trade literature has argued for σ varying at an industry level (Broda et al., 2006; Soderbery, 2015). I write σ_k to denote such an industry-varying trade elasticity. Looking ahead, an important extension of my paper is to redo the estimates with a serious treatment of industry-varying σ. However, I have performed a simple robustness check, and tested a number of ways of solving the problem. Here, I also outline which approaches to this that look relatively more promising.

First, I note that it is possible to use residual plots to detect evidence for industry-varying σ_k. If σ_k is higher than average in an industry, a plot of fitted values and residuals will have a positive slope. Indeed, if a country has high fitted trade values in an industry, it suggests that it has low relative costs. If I use an elasticity for that industry which is too low, the fitted value will be low compared to the actual value. The opposite is true when an industry has a low fitted value of trade. If I have underestimated the trade elasticity, actual values will be even lower than fitted values. These effects mean that an underestimated σ_k leads to a positive relationship between fitted values and residuals on an industry level. Conversely, if I have overestimated σ_k, there will be a negative relationship between fitted values and residual values.

By considering industry-by-industry plots of residuals on fitted values, I can obtain information about industry-specific elasticities. I use this method to perform a simple robustness check by excluding all industries with an absolute value of the residual-fitted plot of more than 1 and I find similar results for this restricted set of industries.

I also run the regression specification

$$\log(x_{i,j}^k) = \delta_{i,j} + \mu_j^k - \sum_{f=2}^{F}[(\sigma_k - 1)\alpha_{US,f}^k]\beta_{i,f} + \varepsilon_{i,j}^k \quad \beta_{US,f} \equiv 0$$

and use different estimates of σ_k across industries. I first use the estimates of industry-specific trade elasticities in Broda et al. (2006). To test whether these help resolve the problem with varying trade elasticities, I analyze whether there is less evidence for industry-varying trade elasticities in the fitted-residual plots when I use the industry-specific estimates σ_k from Broda et al. (2006) compared to when I run the regression with a common elasticity of trade corresponding to their median estimate.

I find that using the industry-specific estimates of trade elasticity do not resolve the problem of correlation between fitted values and residuals on the industry level. If anything, using industry-specific elasticity estimates makes the problem worse.

In addition to using the estimates from Broda et al. (2006), I also try an iterative procedure to more directly bring the fitted-residual plots in line. I run the regression with a common $\sigma_k \equiv \sigma$. I iterate and increase the σ_k whenever the fitted-residual slope in industry k is positive, and decrease σ_k whenever the fitted-residual slope in industry k is negative. Unfortunately, the procedure does not converge.

Using estimates from Broda et al. (2006) and the iterative procedure did not solve the problem with varying trade elasticities. One potential reason for this failure is that it is not theoretically correct to modify regression specification (5) by just changing σ_k. If trade elasticities vary across industries, they also interact with trade cost terms that are now included in the bilateral fixed effect $\delta_{i,j}$. Thus, this will partly depend on industry k, which means that a standard gravity specification with bilateral fixed effects will not work in this context.

Thus, looking ahead, a proper treatment of varying σ_k will require a way of jointly estimating σ_k across industries and modify the structural trade model to generate a regression specification that fully incorporates varying trade elasticities.

D.2 Specification with confounding variables

In Section 5.1, I discuss the effects of an omitted variable bias in my specification of unit costs. Here, I explain how I measure and include potential confounders in my regression specification.

I analyze two confounding variables: external financing sensitivity and contracting sensitivity. I assume that there are country-specific contracting and external financing penalties τ_{cont} and τ_{fin} which capture the general quality of a country's judicial and financial systems. Industries are characterized by a contracting intensity $\alpha^k_{US,con}$ and a external financing intensity $\alpha^k_{US,fin}$. Country-level contracting and financial penalties change log unit costs of industries with $\tau_{cont} \times \alpha^k_{US,con}$ and $\tau_{fin} \times \alpha^k_{US,fin}$, respectively. That is, contracting and financing penalties increase the unit costs of industries in proportion to their respective contracting and external financing intensities.

I define an industry's external financing intensity $\alpha^k_{US,fin}$ as the share of investment expenditure not covered by external financing (external financing share of investments) times the share of gross output devoted to investments. I take the external financing share from Rajan and Zingales (1998), and I measure the investment share of total output using NBER CES data. My definition differs from that in Rajan and Zingales (1998) as I multiply the external financing share of investments with the investment share. The reason is that I interpret the country financial penalty τ_{fin} as a markup on external financing needs. A financing penalty increases the unit costs of an industry in proportion to its external financing needs as a share of gross output. To obtain external financing needs as a share of gross output, I multiply the external financing share of investments with the investment share.

I define an industry's contracting intensity by multiplying two terms. The first term is the share of intermediate inputs expenditure that is sensitive to contracting. To measure this term, I follow Nunn (2007) and use the IO table to calculate the share of intermediate good expenditures that are spent on customized inputs, where I define an input as customized if it is not traded on an exchange nor referenced priced in a trade journal according to the classification of goods in Rauch (1999). The second term in my calculation is the intermediate input cost share, defined as total intermediate good expenditures divided by gross output. I measure this term using NBER CES data. I calculate the contracting intensity $\alpha^k_{US,con}$ as the product of these two terms, i.e. as the product of the share of customized inputs and the intermediate input cost share. My contracting sensitivity method is a slight modification of the measure in Nunn (2007), which only uses the first of my two terms. My modification reflects that I interpret the country contracting penalty τ_{cont} as increasing the cost of contracting sensitive inputs due to the lack of relation-specific investments. The unit cost effect of this is proportional to the total cost of contracting sensitive inputs as a share of gross output. As Nunn's definition only gives the cost of contracting sensitive inputs as a share of intermediate input costs, I multiply his measure with the intermediate input share to obtain my final measure $\alpha^k_{US,con}$.

I include $\alpha^k_{US,con}$ and $\alpha^k_{US,fin}$ in the analysis by adding extra terms to the regression specification

(5), and run the regression

$$\begin{aligned}\log(x_{i,j}^k) &= \tilde{\delta}_{i,j} + \tilde{\mu}_j^k - \sum_{f=2}^{F}[(\sigma-1)\alpha_{f,US}^k] \times \beta_{f,i} \\ &\quad -[(\sigma-1)\alpha_{fin.,US}^k] \times \beta_{fin,i} - [(\sigma-1)\alpha_{con,US}^k] \times \beta_{con,i} + \varepsilon_{i,j}^k.\end{aligned}$$

where $\alpha_{fin.,US}, \alpha_{contr.US}$ give the financial and contracting intensity measured on US data.

D.3 Comparison with unit costs

My unit cost analysis uses the Groningen Growth and Development Center's (GGDC) 2005 benchmark producer price index. This data set aims at providing a cross-country comparable producer price index for 34 industries across 42 countries. The index covers both tradable and non-tradable industries, and manufacturing as well as services (Inklaar and Timmer, 2008).

Following recommendations from a creator of the data set, I exclude financial services, business services, real estate, government, health services and education. For these industries, it is difficult to obtain data on output quantities which makes it difficult to make cross-country comparisons in unit costs. I also exclude "private households with employed persons" as this variable is missing for a large number of countries. After my exclusions, I am left with a total of 27 industries and 35 countries with a complete set of observations.

To obtain factor shares, I use the EU KLEMS data set for the US (as my analysis includes non-manufacturing industries, I cannot use the NBER CES database to obtain factor shares). For the US, EU KLEMS provides data on industry level gross output, labor compensation, and intermediate good compensation. I define the labor share as the labor compensation over gross output, and the intermediate share as the intermediate good compensation over gross output. I calculate the skill share by multiplying the labor share with the share of payroll going to skilled workers with an occupational skill level of 3 or 4. I define the capital share as one minus the other factor shares.

I run the regression

$$\log(c_i^k) = \delta_i + \mu_k + \sum_{f=2}^{F} \alpha_{US,f}^k \tilde{\beta}_{i,f} + \varepsilon_i^k$$

where $\tilde{\beta}_{i,f} = \log\left(\frac{r_{i,f}/r_{i,1}}{r_{US,f}/r_{US,1}}\right)$ captures the deviation of relative prices compared to the US.

I compare the results from the unit cost analysis with the trade data analysis by comparing the relationship between GDP per worker and $\tilde{\beta}_{i,f}$ with the relationship between GDP per worker and $\beta_{i,f}$, where $\beta_{i,f}$ comes from the trade data analysis.[25]

[25] An alternative way to compare the outcomes would be to regress $\beta_{i,f}$ on $\tilde{\beta}_{i,f}$ and test how close the results are to a 45 degree line. I have chosen my method as I am interested in broad correlations between skilled service prices and GDP per capita, and given the estimation errors in the skill price estimates, regressing them on each other biases the

In Figures 8 and 9, I plot the results from the unit cost data analysis. The slope parameter of log relative skilled service prices on log GDP per worker is -1.19 using the unit cost data, and -1.53 using the trade data method for the same set of countries. I cannot reject that the two coefficients are equal, even without taking into account the large standard errors on the unit costs based parameters $\tilde{\beta}_{i,f}$. Thus, when both types of data exist, the trade data method and the unit cost method paint a similar picture of the relationship between relative skilled service prices and GDP per worker.

D.4 Differences in unskilled human capital quality Q_u

In the current setup, I estimate the quality of unskilled labor Q_u by assuming that unschooled labor is of equal quality and that improvements are reflected in Mincerian returns:

$$Q_{U,i} = \exp(\phi(S_{U,i}))$$

where ϕ is a Mincerian return function and $S_{U,i}$ is the average schooling time of unskilled labor.

A number of papers on human capital and development accounting have stressed that there might be uniform quality differences in human capital (Caselli, 2005; Manuelli and Seshadri, 2014). These quality differences might reflect differences in nutrition, health, or the quality of early schooling.

As my paper estimates Q_u and Q_s/Q_u any uniform increase in Q_u will also increase Q_s proportionally.

results down due to measurement error. Regressing $\beta_{i,f}$ on $\tilde{\beta}_{i,f}$ and regressing $\tilde{\beta}_{i,f}$ on $\beta_{i,f}$ both yield a regression coefficient of less than one.