Human Capital and Development Accounting Revisited*

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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 data on international manufacturing exports. My method exploits the negative relationship between relative prices of skilled labor services and relative export values in skill-intensive industries. Depending on the assumed trade elasticity, the relative efficiency-adjusted price of skilled and unskilled labor services is 5-30 times lower in rich countries compared to in poor countries, with an estimated 9 times difference for the middle of the range of trade elasticities. When I use these estimates to decompose productivity differences in manufacturing, TFP differences in manufacturing falls from a factor of 4.3 to a factor of 2.0-3.0. Instead, skilled labor efficiency differences become more important. Under an assumption of neutral technology differences, like in traditional development accounting, the skilled labor efficiency differences reflect human capital quality differences. If the assumption of skill-neutral technology differences is relaxed, an alternative explanation is that there are large skill-biased technology differences between rich and poor countries.

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1 Introduction

In growth and development economics, an influential view is that productivity 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 productivity 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 than productivity levels across countries, and that large uniform labor efficiency differences are needed to explain productivity 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 productivity 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 arises as imperfect substitutability implies that skilled labor services have relatively low prices in rich countries, which, in turn, 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 the skilled wage premium can be decomposed as a product of relative efficiencies of skilled workers

[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 productivity differences across countries. However, they differ in their interpretation of these efficiency differences. B Jones (2014a) interprets them as reflecting a high human capital level of skilled workers in rich countries, whereas Caselli and Coleman (2006) and Caselli (2016) interpret them as reflecting skill-biased technological differences.

and relative prices of skilled labor services:

$$\frac{w_s}{w_u} = \frac{Q_s}{Q_u}\frac{r_s}{r_u}, \tag{1}$$

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, the relative efficiency-adjusted price of skilled and unskilled labor services is 5-35 times lower in rich countries compared to in poor countries, with an estimated 9 times difference for the middle of the range of trade elasticities. Even though rich countries have lower skilled wage premia than poor countries, this cannot fully explain the low revealed 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 use the trade-based estimates to decompose productivity differences in the manufacturing sector. I show that if industry production technology differences take a factor-augmenting form, there exists an aggregate production function for the manufacturing sector that can be expressed as a TFP-term times a function of efficiency-adjusted factor supplies. In this setting, there also exists a well-defined notion of efficiency-adjusted factor service prices in the sense that a) observed factor prices, efficiency-adjusted factor prices, and factor efficiency terms are related by the equation (1), and b) relative unit production costs across sectors are determined by the efficiency-adjusted factor prices. The first point implies that efficiency-adjusted factor prices can be used to derive relative factor-efficiencies from observed factor prices, and the second point implies that the trade-based estimates can be used to identify relative efficiency-adjusted prices.

Having identified the factor efficiency terms, it is possible to perform a chained TFP-calculation, where the total TFP difference between rich and poor countries is calculated by dividing countries into income groups, and the total TFP difference is calculated by aggregating the TFP differences between neighboring income groups. To calculate the TFP difference between income groups, I use the standard result that TFP differences can be approximated to a second-order degree by subtracting a Divisia index of efficiency-adjusted factor intensity differences from the log difference in worker productivity. This method allows us to calculate TFP differences without taking a stand on the functional form of the aggregate production function in manufacturing.

Applying this, I find a factor of 5.12 in uniform TFP differences when I do not adjust for labor quality. When I adjust for labor quality assuming perfect substitutability, the TFP differences falls to 4.3, and when I allow for imperfect substitutability by integrating the trade-estimates, the TFP differences fall further to 2.0-3.0. Thus, allowing for imperfect substitutability reduces the role of TFP differences in explaining productivity differences.

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.

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 one estimate of human capital differences among skilled workers using summary statistics on wage changes at migration from Hendricks and Schoellman (2017). I focus on their large sample of primarily skilled Indian migrants. We can use this sample to estimate the relative quality of Indian and US skilled worker by estimating the relative quality of American skilled workers and Indian migrants by their observed relative wages in the US, and the relative quality of Indian migrants and average Indian workers by the ratio of pre-migration wages in India and the wages of skilled non-migrants in India. By multiplying these two terms, we obtain the average relative quality of American and Indian skilled workers.[4]

Applying this analysis, I find a 4 times difference in the average quality of skilled workers between the US and India. This is consistent with the quality differences found in the trade analysis for a trade elasticity of approximately $\sigma = 10$. To explain the larger factor efficiency differences found for lower values of the trade elasticity, we need some combination of complementarities between

[4]This analysis neglects the role of occupational switching and potential complementarities between skilled workers, but it can estimate the quality differences between skilled workers when it is assumed that the comparative advantage of migrants do not change, and when quality differences take the form of workers supplying different amounts of internally homogeneous skilled service.

heterogeneous types of skilled workers, changing comparative advantage for migrants, and skill-biased technology differences.

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 compares the trade results with an approach using unit production cost data, 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 (2010), 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 the method for resolving the non-tradable component of the intermediate input cost share into cost shares of other inputs using an input-output table.

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	0.31	0.05
Skilled labor	0.25	0.25
Capital	0.13	0.34
Traded intermediate inputs	0.31	0.32
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, 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 $I = 90$ countries, and each country has $K = 84$ industries, corresponding to the NAICS four-digit manufacturing industries.[6] 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 $F = 4$ factor services. In my baseline analysis, these are services from unskilled labor, skilled labor, capital, and traded intermediate inputs.

[6]The countries correspond to the 89 countries with total manufacturing exports exceeding \$1bn USD, and with a GDP per worker higher than \$5,000. The rest of the countries are aggregated to "Rest of the World". I focus on manufacturing industries since the variety-based trade models underlying my estimation procedure are likely to be most relevant for manufacturing.

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

I assume that differences in production technologies and factor qualities across countries take a factor augmenting form. That is, I assume that there exists a set of industry production functions F^k and factor-efficiency terms $Q_{i,f}$ such that country-specific industry production functions F_i^k can be written as

$$F_i^k(x_{i,1}^k, \ldots, x_{i,F}^k) = \tilde{A}_i F^k(Q_{i,1}x_{i,1}^k, \ldots, Q_{i,F}x_{i,F}^k).$$

This implies that the unit production cost of a good k in country i can be written as

$$c_i^k = \frac{C^k(r_{i,1}, \ldots, r_{i,F})}{\tilde{A}_i},$$

where C^k is common across countries (and dual to F^k), and where $r_{i,f}$ are efficiency-adjusted factor service prices. These efficiency-adjusted prices will be a key object of analysis.

2.2 Key equations

My estimation builds on the following two equations:

$$\log(x_{i,j}^k) = \delta_{i,j} + \mu_j^k + \sum_{m=1}^{M} \gamma_m^k d_{ij,m} - (\sigma - 1)\log(c_i^k) \tag{2}$$

$$\log(c_i^k) = \log(c_{US}^k) + a_i + \sum_{f=2}^{F} \left(\frac{\alpha_{US,f}^k + \alpha_{i,f}}{2} \right) \log\left(\frac{r_{i,f}/r_{i,1}}{r_{US,f}/r_{US,1}} \right), \tag{3}$$

where $a_i = \log\left(\frac{r_{i,1}}{r_{US,1}}\right) - \log\left(\frac{\tilde{A}_i}{\tilde{A}_{US}}\right)$ 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 four 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 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 represents industry-specific coefficients on a set of gravity terms, allowing for heterogeneous trade costs across industries. The fourth term captures that conditional on the first three terms, 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 a second order approximation of industry unit costs around the US cost structure, where $f = 1$ indexes unskilled labor services. I obtain the approximation by noting that if the common unit cost function C^k has a translog form, then competitive factor markets imply that

$$\begin{aligned} \log(c_i^k) - \log(c_{US}^k) &= \left[\log C^k(r_{i,1}, \ldots, r_{i,F}) - \log C^k(r_{i,1}, \ldots, r_{i,F})\right] + (\log \tilde{A}_{US}) - \log \tilde{A}_i) \\ &= \sum_{f=1}^{F} \left(\frac{\alpha_{US,f}^k + \alpha_{i,f}^k}{2}\right) \log\left(\frac{r_{i,f}}{r_{US,f}}\right) + (\log \tilde{A}_{US} - \log \tilde{A}_i), \end{aligned}$$

where $\alpha_{i,f}^k$ is the industry factor shares in country i. I obtain equation (3) by extracting the term involving unskilled labor services, and using that factor shares sum to 1. This allows me to focus on the *relative* price of factor services compared to unskilled labor services. Since the translog cost function is a second-order approximation to any cost function, this provides a second-order approximation to deviations in relative unit costs from the US, regardless of the underlying industry unit cost function C^k.

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 the average of US and country i 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.

2.3 Regression specification

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

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

Here, $\tilde{\delta}_{i,j} = \delta_{i,j} - (\sigma - 1)\left(\log\left(\frac{r_{i,1}}{r_{US,1}}\right) - \log\left(\frac{\tilde{A}_i}{\tilde{A}_{US}}\right)\right)$ 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 use measure gravity terms from standard data sets, 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.[7] I lack direct measures on factor shares on a detailed industry level across many countries, so I approximate $\alpha_{i,f}^k$ by using the detailed US estimates in combination with more aggregated international measures on labor, capital, and skilled and unskilled labor shares.

Thus, $\log(x_{i,j}^k)$ is my left-hand variable, and $(\sigma - 1)\frac{\alpha_{US,f}^k + \hat{\alpha}_{i,f}^k}{2}$ 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:

$$\log(x_{i,j}^k) = \tilde{\delta}_{i,j} + \mu_j^k + \sum_{m=1}^{M} \gamma_m^k d_{ij,m} - \sum_{f=2}^{F} \left[(\sigma - 1)\frac{\alpha_{US,f}^k + \hat{\alpha}_{i,f}^k}{2}\right] \times \beta_{i,f} + \varepsilon_{i,j}^k, \tag{4}$$

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, a set of gravity variables with industry-specific coefficients, and $-(\sigma - 1)\frac{\alpha_{US,f}^k + \hat{\alpha}_{i,f}^k}{2}$ for $f = 2, \ldots, F$, allowing for country-factor specific parameters $\beta_{i,f}$. In total, I estimate $(4 - 1) \times 90 = 270$ 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 parameter $\beta_{i,skill}$ identifies the difference to the US in the log relative price of skilled labor services.

2.4 Data in trade regression

The regression equation (4) requires data on bilateral trade flows $x_{i,j}^k$, gravity terms $d_{ij,m}$, US factor shares $\alpha_{US,f}^k$, estimates of international factor shares $\alpha_{i,f}^k$, 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

[7] 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.

(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 BEA 2007 input-output table with data from the Occupational Employment Statistics (OES) survey. The BEA reports labor compensation and intermediate input shares as a share of gross output, and I define the capital share as one minus the labor and intermediate input share. 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.[8]his corresponds to the major occupational groups "Managers", "Professionals", and "Technicians and Associate Professionals". I calculate the skill share as the labor share from the BEA 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. Furthermore, to obtain the full domestic capital, skilled, and unskilled content in an industry, I resolve the non-traded intermediate factor share into its constituent parts (including traded intermediate inputs). The final shares thus represent unskilled labor, skilled labor, capital, and tradable intermediate inputs. Appendix A.3 describes the method for resolving non-traded intermediate input shares into their constituent components.

To estimate the international factor shares $\alpha_{i,f}^{k}$, I use international factor shares data on a higher level of aggregation. The World Input Output Database reports labor and intermediate input compensation shares in manufacturing across 42 countries. I regress these compensation shares on GDP per capita to create a predicted labor, capital, and intermediate input compensation shares for each country (normalizing so that the US obtains the compensation shares observed in the BEA). I similarly create a predicted split of labor compensation into skilled and unskilled labor shares by using IPUMS data on the occupational composition and relative wages in manufacturing.[9]

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. The OES occupational data is recorded according to SOC, and they are converted to ISCO-08 to calculate the share of payroll going to skilled workers. The BEA data is recorded in the Input-Output coding scheme. All factor share and trade data are converted between coding schemes using a concordance procedure described in Appendix E.

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

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[9]In general, correcting for different factor shares across countries does not change the main results considerably. I have also experimented with using more detailed Colombian factor shares data, which makes the result somewhat stronger, but do not change them considerably either.

destination country. Thus, the relevant elasticity is the long-run elasticity between different foreign varieties. The higher the σ, the lower is the importance of skilled labor efficiency differences since it reduces the required differences in relative efficiency prices required to explain trade patterns.

I vary the trade elasticity between $\sigma = 5$ and $\sigma = 10$. This reflects a range of estimates found in the literature. Simonovska and Waugh (2014) report $\sigma = 5$, Costinot et al. (2011) use $\sigma = 7.2$ and Eaton and Kortum find $\sigma = 9.2$ found in Eaton and Kortum (2002).[10] $\sigma = 10$ corresponds to the higher range estimates found in Romalis (2007) when he estimates the trade effects of NAFTA. Unless stated otherwise, I report the results for $\sigma = 7.5$.

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, for randomly selected countries in different income categories.

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.

My primary interest is in the relative prices of skilled services, and the pattern of relative prices of skilled labor services with income is summarized in Table 5 for different values of the trade elasticity σ. We see that the poorest countries have approximately 4 to 30 times higher relative prices of skilled labor services to rich countries in efficiency-adjusted terms.

In Figure 1, I provide a graphical illustration of the same relationship between on a log scale. The relative price of skilled labor services in countries with more than $75,000 in GDP per capita is normalized to 1. There is a negative relationship, that is approximately linear, with some exceptions of poor countries with low estimated relative prices of skilled serivces (e.g. the Philippines and Costa Rica), and some exception with rich countries that have relatively high estimated skill prices (e.g. the oil countries).

3 Development accounting

In this section, I want to use the estimates from Section 2 to decompose productivity differences in manufacturing. The aim is to find the size of uniform TFP differences in manufacturing between rich and poor countries. I focus on manufacturing as the trade estimates are based on manufacturing trade data, which means that I only need to extrapolate from the traded sector to the overall

[10]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: Trade regression results in abridged form

	Skill	Capital	Tradable intermediate inputs
Output per worker \$5,000-\$15,000			
India	2.924 (1.660)	1.715 (0.380)	2.498 (0.817)
Republic of Moldova	4.196 (1.767)	1.778 (0.498)	1.885 (0.940)
Honduras	5.692 (1.886)	1.654 (0.465)	2.919 (0.938)
Peru	4.016 (1.497)	1.694 (0.447)	1.672 (0.847)
Output per worker \$15,000-\$30,000			
Sri Lanka	4.798 (1.619)	2.649 (0.534)	3.585 (0.861)
Ukraine	2.422 (1.425)	1.056 (0.442)	0.687 (0.780)
Uruguay	3.014 (1.395)	0.958 (0.491)	0.713 (0.800)
Dominican Republic	2.928 (1.441)	0.851 (0.453)	1.954 (0.754)
Output per worker \$30,000-\$50,000			
Chile	3.270 (1.350)	0.474 (0.424)	0.073 (0.722)
Malaysia	−0.198 (1.279)	0.576 (0.452)	0.535 (0.700)
Algeria	2.247 (1.207)	−0.268 (0.568)	−0.213 (0.691)
Trinidad and Tobago	2.692 (1.213)	0.309 (0.475)	0.438 (0.659)
Output per worker \$50,000-\$75,000			
New Zealand	0.938 (1.199)	0.491 (0.460)	−0.142 (0.839)
Greece	3.272 (1.094)	1.195 (0.387)	1.604 (0.619)
Republic of Korea	0.165 (1.204)	0.941 (0.486)	0.780 (0.726)
Japan	−0.853 (1.269)	0.130 (0.558)	0.190 (0.793)
Output per worker >\$75,000			
Germany	0.690 (1.055)	0.420 (0.378)	0.522 (0.569)
Sweden	0.292 (1.160)	0.416 (0.464)	0.367 (0.634)
Netherlands	0.209 (1.012)	−0.292 (0.361)	−0.264 (0.555)
Macao	3.361 (1.140)	2.302 (0.584)	3.113 (0.741)
USA	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Observations	367306		
R^2	0.6899		

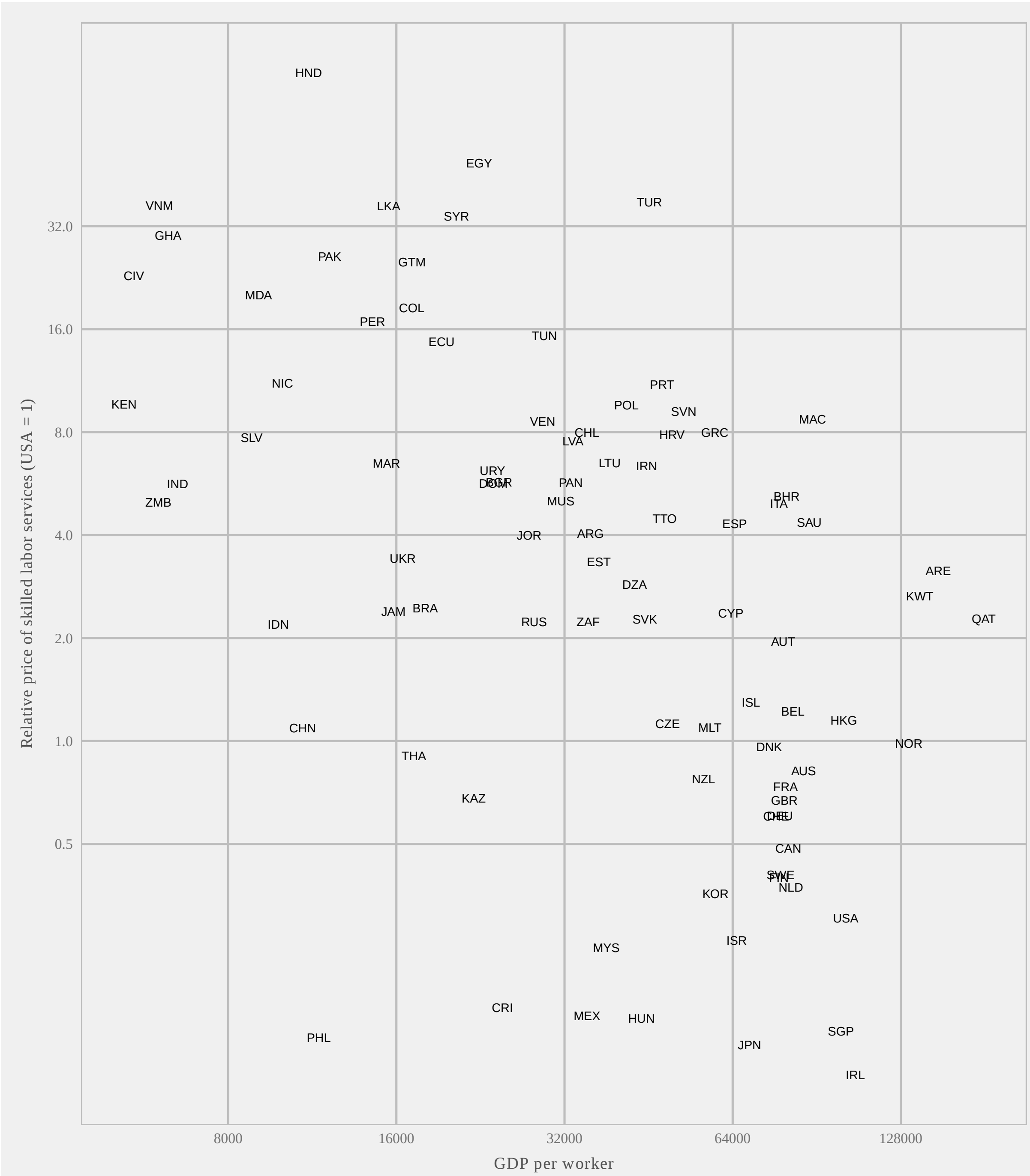


Figure 1: GDP per worker and

GDP per worker range	$\sigma = 5$	$\sigma = 7.5$	$\sigma = 10$
5,000-15,000	34.44	8.83	4.82
15,000-30,000	16.93	5.70	3.52
30,000-50,000	6.66	3.21	2.32
50,000-75,000	1.40	1.23	1.16
>75,000	1.00	1.00	1.00

Table 5: Relative price of skilled and unskilled labor services for different trade elasticities

manufacturing sector, and not from the manufacturing sector to the rest of the economy.[11]

3.1 Aggregate production function

Performing development accounting requires more theoretical structure on the aggregate manufacturing sector. In Section 2, the key assumption was that trade flows followed a gravity relationship. However, this assumption is consistent with a range of models for the aggregate manufacturing sector. In contrast, to perform a development accounting exercise, we need an aggregate production function that takes a factor-augmenting form. Furthermore, we need to connect the estimates from the trade data analysis to the factor-augmenting terms in the aggregate production function.

Concerning the existence of an appropriate aggregate production function, it can be shown that a constant-returns to scale aggregate production function exists under relatively weak assumptions in standard trade models (see Appendix B.2). Furthermore, it is possible to prove (see below) that if the industry-level production functions can be expressed in a factor-augmenting form, then the aggregate production inherits this property. More formally, suppose that there exists factor-augmenting efficiency terms $Q_{i,f}$ such that country-industry production functions F_i^k satisfy

$$F_i^k(x_{i,1}^k, \ldots, x_{i,F}^k) = \tilde{A}_i F_i^k(Q_{i,1}x_{i,1}^k, \ldots, Q_{i,F}x_{i,F}^k)$$

for some country-specific productivity terms $\tilde{A}_i$, and for a set of production functions F^k that are common across countries. Then, if G_i is the aggregate production function for manufacturing in country i, we can write

$$G_i = A_i G(Q_{i,1}x_{i,1}, \ldots, Q_{i,F}x_{i,F})$$

for some function G and TFP-levels A_i.

The second step is to connect this aggregate production function to the trade estimates. To do this, we note that once we have represented the aggregate manufacturing sector in a factor-augmenting form, then there exists a well-defined notion of efficiency-adjusted factor service prices $\tilde{r}_{i,1}, \ldots, \tilde{r}_{i,F}$. These quantities are efficency-adjusted factor prices in the following two senses.

[11] This leads me to find a smaller effect of allowing for imperfect substitutability, because there is a lower skilled labor share in manufacturing compared to the overall economy.

First, the relative prices $\tilde{r}_f/\tilde{r}_{f'}$ give the marginal rate of transformation of the aggregate production function $A_i G$ with respect to effective factor inputs. As a corollary, relative efficiencies $Q_f/Q_{f'}$, relative observed factor prices $w_f/w_{f'}$, and relative efficiency-adjusted factor prices $\tilde{r}_f/\tilde{r}_{f'}$ are connected through the equation

$$\frac{w_f}{w_{f'}} = \frac{Q_f}{Q_{f'}}\frac{\tilde{r}_f}{\tilde{r}_{f'}}.$$

The set of prices $\{\tilde{r}_{i,f}\}$ are also efficiency-adjusted factor service prices in the sense that they govern the relative unit costs across industries. More formally, when industry production functions take a factor-augmenting form, there exists a set of unit costs functions c^k that are common across countries (and dual to the common industry production functions F^k) such that the unit production costs in country i, industry k are

$$c_i^k = \frac{c^k(\tilde{r}_{i,1}, \ldots, \tilde{r}_{i,F})}{\tilde{A}_i}.$$

Thus, $\{\tilde{r}_{i,f}\}$ govern the relative unit cost variation across industries.

The connection between $\{r_{i,f}\}$ and unit costs implies that we can use the trade data estimates to identify the relative effective factor service prices $\tilde{r}_{i,f}/\tilde{r}_{i,f'}$. Indeed, in Section 2, the key assumption on unit costs was that they could be written on the form above. In this case, if c^k has a translog form for each k, then the trade estimates identify the relative effective factor service prices in the aggregate production function. Furthermore, as a translog cost function is a second-order approximation to an arbitrary unit cost functions, the trade estimates capture the relative efficiency-adjusted factor service prices up to a third-order specification error in the unit cost function even if c^k is not translog.

The reasoning above is formalized in the following theorem.

Theorem 1. *Assume that there exists a set of country-common industry production functions F^k, and a set of factor-augmenting efficiency differences $Q_{i,f}$ for $i = 1, \ldots, I$, $f = 1, \ldots, F$ such that*

$$F_i^k(x_{i,f}^k, \ldots, x_{i,F}^k) = A_i F^k(Q_{i,f} x_{i,f}^k, \ldots, Q_{i,F} x_{i,F}^k) \quad \forall i, k.$$

If factor markets are competitive, there exists a function G, a set of efficiency-adjusted prices $r_{i,f}$, a set of industry unit costs functions c^k, and a set of TFP-levels A_i, such that

1. *Aggregate output in country i is given by*

$$Y_i = A_i G(Q_{i,1} x_{i,1}, \ldots, Q_{i,F} x_{i,F})$$

2. *Relative prices $r_{i,f}/r_{i,f'}$ satisfy*

$$\frac{r_{i,f}}{r_{i,f'}} = \frac{G_f}{G_{f'}}$$

3. *Factor efficiencies $Q_{i,f}$, factor prices $w_{i,f}$, and efficiency adjusted factor prices $r_{i,f}$ are related*

by

$$\frac{r_{i,f}}{r_{i,f'}} \frac{Q_{i,f}}{Q_{i,f'}} = \frac{w_{i,f}}{w_{i,f'}}$$

4. *Industry unit costs functions in country i are given by*

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

where c^k is the unit cost function associated with the production function F^k.

Proof. See Appendix B.3. □

3.2 Chained TFP calculations

The previous section demonstrated that when industry production functions take a factor-augmenting form, we can express aggregate manufacturing output as a function

$$Y_i = A_i G(Q_u U, Q_s S, Q_k K),$$

and we can use can use the trade-based estimates of relative efficiency-adjusted factor service prices r_f/r_1 to back out factor-efficiency adjusters via the equation

$$\frac{w_f}{w_1} = \frac{r_f}{r_1} \frac{Q_f}{Q_1},$$

where w_f are the observed factor prices. By using an independent method to estimate a baseline factor efficiency Q_1 (in our case, this will be the quality of unskilled labor), we can obtain estimates of $Q_{i,1}, \ldots, Q_{i,F}$ for all countries. This gives us the efficiency-adjusted factor inputs across all countries.

In the development accounting literature, the standard approach to decompose productivity differences, given observed factor supplies and an aggregate production function G, has been to make a functional form assumption on G. Standard assumptions have been that G is a Cobb-Douglas aggregator of labor and capital with linear aggregation of labor (Hall and Jones, 1999; Caselli, 2005; Jones, 2015), or a Cobb-Douglas aggregator of capital and labor with a CES aggregator of labor (Caselli and Coleman, 2006; Jones, 2014a; Caselli, 2016).

The problem with applying these two approaches to my productivity accounting exercise is that the labor share is not constant in manufacturing. One approach to this problem is to pose another functional form for the aggregate production function that addresses these issues, but it is also possible to solve it by applying non-parametric tools from the growth accounting literature.

In particular, when aggregate output per worker satisfies

$$\frac{Y_i}{L_i} = A_i G\left(\frac{Q_{i,1}x_{i,1}}{L_i}, \dots, \frac{Q_{i,F}x_{i,F}}{L_i}\right),$$

then the second order approximation to output deviations under competitive markets is

$$\log\left(\frac{Y_i}{Y_{i'}}\right) = \log\left(\frac{A_i}{A_{i'}}\right) + \sum_{f=1}^{F}\left(\frac{\alpha_{i,f}+\alpha_{i',f}}{2}\right)\log\left(\frac{Q_{i,f}x_{i,f}}{Q_{i',f}x_{i',f}}\right),$$

where $\frac{\alpha_{i,f}+\alpha_{i',f}}{2}$ denotes the average factor share of factor f in countries i and i' (Diewert, 1974). By re-arranging the equation, the TFP difference between the two countries can be estimated using data on relative output per workers, relative efficiency-adjusted factor supplies, and factor shares.

I use this result to create a chained TFP calculation exercise between different income groups $g = 1, \dots, G$. For each income group g, define the difference in TFP to next income group as

$$\log\left(\frac{\bar{A}_g}{\bar{A}_{g-1}}\right) = \log\left(\frac{\bar{Y}_g}{\bar{Y}_{g-1}}\right) - \sum_{f=1}^{F}\left(\frac{\bar{\alpha}_{f,g}+\bar{\alpha}_{f,g-1}}{2}\right)\log\left(\frac{\bar{Q}_{f,g}\bar{x}_{f,g}}{\bar{Q}_{f,g}\bar{x}_{f,g-1}}\right)$$

where all factor shares with g subscripts are simple averages, and all other variables with g subscripts are geometric averages.

By using this expression, it is possible to decompose the differences in TFP across different income groups without placing strong functional form assumptions on the aggregate manufacturing sector.

3.3 Data and estimates

In my accounting exercise, I use three factors of production: unskilled labor, skilled labor, and capital services. Thus, I need information about manufacturing output per worker y_{man}, capital per worker k_i, share of skilled and unskilled workers s_i and s_i, efficiency adjusters $Q_{u,i}$, $Q_{s,i}$, and $Q_{k,i}$, factor shares $\alpha_{u,g}$, $\alpha_{s,g}$, and $\alpha_{k,g}$. I define the income groups by GDP per worker in 2005 (output-based PPP from PWT 9.0).

GDP per output ranges	Number of countries in the WIOD
5,000-15,000	3
15,000-30,000	4
30,000-50,000	10
50,000-75,000	8
$>$75,000	15

Table 6: Output per worker groups and number of countries

The definition of the income groups is displayed in Table 6. The subdivisions are chosen with reference to data availability in the WIOD, which is the source of the data on factor shares, capital intensity, and manufacturing output per worker. The subdivisions reflect a trade-off between having as large a number of countries as possible in each bin, while keeping the bins as small as possible. The small set of poor countries in the WIOD makes it potentially problematic to use the trade estimates for this set of countries, as the trade estimates are estimated with error. Thus, for the trade estimates, I use the average of all observations in each respective income group.

To measure manufacturing output per worker, I use the WIOD data to obtain total manufacturing employment and value added in local prices for 2005. I deflate the local currency manufacturing output using a manufacturing producer price PPP exchange rate. I create it by combining the PWT 9.0. 2005 market exchange rate with the production-side manufacturing price level constructed in Inklaar and Timmer (2013).

To construct the employment share of unskilled and skilled labor, I use census data and labor force survey data from IPUMS for the set of countries with 2005 GDP per worker greater than \$5,000 and an available data set after 2000 which records industry and occupation of workers. I calculate the share of manufacturing workers that have an occupation in any of the ILO categories "Professionals", "Technicians and associate professionals", or "Legislators, senior officials and managers". These are the occupations which have skill level 3 or 4 according to ILO's definition, and this definition is consistent with the skill definition in the trade data. Note that I use an occupational definition of skill. This choice is discussed in Appendix C.1.

For each country, I use the WIOD to measure the labor share in the manufacturing sector as total labor compensation divided by value added, and then I define the labor income share α_g for the income group as the average of country labor shares. The capital share $\alpha_{k,g}$ is defined as 1 minus the average labor share in group g.

To split the labor share into compensation of skilled and unskilled workers, I combine information on the relative supply of skilled and unskilled workers with data on the skilled wage premium. The method for deriving the relative supply of skilled services was described before. The skilled premium is also measured using IPUMS data. Unfortunately, less countries record income data on occupation/industry level in IPUMS. Thus, my sample is restricted to Brazil, Canada, Dominican Republic, India, Indonesia, Jamaica, Mexico, Panama, South Africa, and the USA. Thus, I calculate the average wage premia in each income group by regressing the log wage premia on log output per worker and using the average predicted value for each range of GDP values. Using the relative supply of skilled and unskilled workers s_g/u_g and the skilled wage premia $w_{s,g}/w_{u,g}$, the relative factor share of skilled and unskilled workers labor can be defined by

$$\frac{\alpha_{s,g}}{\alpha_{u,g}} = \frac{s_g}{u_g}\frac{w_{s,g}}{w_{u,g}}.$$

I measure the relative efficiency of skilled versus unskilled labor Q_s/Q_u by

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

where I obtain r_s/r_u from the trade data estimates. To calculate the group averages, I log both sides of the expression and take the averages over countries in each income group. I consider the results both when the average of trade estimates are taken over all countries with trade estimates, and over the countries available in the WIOD.

It is theoretically possible to use the trade data estimates to estimate the relative efficiency of capital and unskilled labor

$$\frac{w_k}{w_u} = \frac{Q_k}{Q_u}\frac{r_k}{r_u}.$$

However, this would require us to know the user cost of capital w_k in the economy, which is not directly observed. Thus, I set Q_k to be constant across countries in the baseline.

Lastly, I define the quality of unskilled labor Q_u through a standard Mincerian method where I use the average education length among unskilled workers in manufacturing, and then measure Q_u by converting workers to unskilled equivalent units assuming a Mincerian return of 10%, motivated by Banerjee I use the IPUMS data to obtain data on the educational level among manufacturing workers, and define the length of primary school as 6 years, the length of secondary school as 12 years, and the length of college as 15 years.

3.4 Results

In Table 7, I report the key summary statistics of the development accounting exercise (for $\sigma = 7.5$). The first column shows average output per worker for the countries in the WIOD in each income range. The second column shows manufacturing output per worker. This shows that differences in manufacturing output are about of the same size as differences in overall output. The third column shows the capital output ratio in manufacturing, which is somewhat higher in lower income groups. The share of skilled workers in manufacturing is increasing with income, and goes from approximately 10% of the number of workers to 30% of workers. The wage premium is higher in poor countries, but not dramatically higher – only a factor of 1.5. In contrast the relative efficiency-adjusted of skilled labor services is almost 9 times higher. Combining these two facts imply that the relative quality of skilled and unskilled labor is 5.5 times lower in poor countries compared to in rich countries. The last column shows human capital calculated by linear aggregation, i.e. by taking converting skilled workers to unskilled workers using the skilled wage premium, and then multiplying by the quality of unskilled workers.

In Table **??**, I report the variables that are directly used in the accounting exercise. Note that the capital share α_k is considerably higher for poor countries than for rich countries, making the assumption of a Cobb-Douglas aggregator between capital and labor inappropriate for this

GDP/worker	y	y_{manuf}	K_m/Y_m	s_m	w_s^m/w_u^m	r_s^m/r_u^m	Q_s^m/Q_u^m	h
5,000-15,000	8856	7380	3.04	0.09	3.53	8.82	0.40	2.65
15,000-30,000	23686	9403	3.50	0.15	2.98	5.70	0.52	2.93
30,000-50,000	41244	20783	2.46	0.16	2.66	3.21	0.83	2.96
50,000-75,000	62280	41263	2.55	0.29	2.44	1.22	2.00	3.90
>75,000	82997	81199	1.39	0.31	2.14	1.00	2.14	3.77

Table 7: Summary statistics for development accounting exercise

situation.

Table 9 displays the result of the development accounting exercise. I write $\Delta_m = \log(y_{man,g}) - \log(y_{man,g-1})$ for the difference in manufacturing output between two income groups. I write $\gamma_x = \frac{\alpha_{x,g-1}+\alpha_{x,g}}{2}\log(xQ_x)$ for the Divisia index for the factor-efficiency adjusted factor input between two groups. For the linear human capital aggregator h, I define $\alpha_h = 1 - \alpha_k$ as the total labor share. The last three columns represent three different ways of measuring TFP. The first TFP measure does not adjust for quality of labor at all, and only subtract the capital contribution. The second TFP measure is the standard TFP measure from the development accounting literature, which uses a linear aggregator of labor input. The third TFP measure with imperfect substitutability between different labor services.

The second to last line sums each column, and shows the relative contribution of different factor inputs, as well as total log TFP differences. The last line is the exponent of the second to last line. Output differences are a factor of 11. When there is no correction for labor quality, a factor of 5 depends on TFP differences. This is reduced to 4.3 using the traditional correction, but only to approximately 2.6 when imperfect substitutability is taken into account. Thus, the introduction of imperfect substitutability decreases the importance of uniform TFP differences in explaining manufacturing productivity differences.

Lastly, Table 10 shows how the results depend on the trade elasticity σ. The first column shows the calculated TFP ratios between rich and poor countries. We see that the higher σ is, the larger are the required TFP differences. When $\sigma = 5$, there is only a factor 2 in TFP differences. When $\sigma = 10$, the TFP ratio is instead 3. The mechanism underlying this is that a higher σ reduces the estimated difference in efficiency of skilled labor across countries. This is shown in the second column. For $\sigma = 5$, there is a 27 times difference in the efficiency of skilled workers, but for $\sigma = 10$, this is reduced to only approximately 4.

$\log(y_{manuf})$	$\log(uQ_u)$	$\log(sQ_s)$	$\log(K/L)$	$\log(h)$	α_s	α_k	NA
8.91	0.67	-2.49	10.02	0.99	0.25	0.10	0.65
9.15	0.65	-1.70	10.40	1.08	0.33	0.18	0.49
9.94	0.67	-1.14	10.84	1.09	0.34	0.18	0.48
10.63	0.66	0.48	11.56	1.37	0.31	0.32	0.37
11.30	0.64	0.64	11.64	1.33	0.32	0.31	0.37

Table 8: Productivity accounting variables

$\log(y_m)$	Δ_{y_m}	γ_u	γ_s	γ_k	γ_h	$(\Delta_{y_m} - \gamma_k)$	$(\Delta_{y_m} - \gamma_k - \gamma_h)$	$(\Delta_{y_m} - \gamma_k - \gamma_u - \gamma_s)$
8.91								
9.15	0.24	-0.01	0.11	0.22	0.05	0.03	-0.02	-0.08
9.94	0.79	0.01	0.10	0.22	0.01	0.58	0.57	0.47
10.63	0.69	-0.00	0.40	0.31	0.17	0.38	0.22	-0.02
11.30	0.68	-0.01	0.05	0.03	-0.02	0.65	0.67	0.61
Log	2.40	-0.01	0.66	0.76	0.20	1.63	1.45	0.98
Ratio	11.00	0.99	1.94	2.15	1.22	5.12	4.27	2.66

Table 9: Decomposition of productivity differences

4 Interpretation of mechanism: High efficiency of skilled labor

4.1 Mechanism

Section 3 showed that my method of aggregating human capital attributes a smaller role to uniform TFP differences in accounting for productivity differences than traditional development accounting methods do. Instead, there is a larger role for differences in the efficiency of skilled labor. This is visible in Table 7, where we see that a higher skilled wage premium cannot fully account for the high efficiency-adjusted relative price of skilled labor services in poor countries. This leads us to impute that there are skill-biased efficiency differences between rich and poor countries.

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

	TFP	Q_s^{rich}/Q_s^{poor}
$\sigma = 5$	1.98	27.00
$\sigma = 7.5$	2.66	6.92
$\sigma = 10$	3.03	3.78

Table 10: Development accounting results for different σ

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.[12]

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

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

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 results depend on large differences in the quality of skilled labor between rich and poor countries. The interpretation of the results depends on the source 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, the results suggest an increased importance of human capital in explaining income 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.

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

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 variation in the quality of skilled labor across countries. Using data on wage gains for migrants from India to the US, I estimate that the average quality of skilled labor about 4 times as high in the US compared to India. This is based on Indian migrants to the US having approximately 1.5 times lower wages than American workers, while the migrants had 2.5 the Indian skilled worker wage level before leaving India.

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.[13]

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

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

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 human capital in explaining skilled labor efficiency differences.[14]

I analyze the case of India, where Hendricks and Schoellman (2017) have sufficiently rich data to report both pre- and post-migration wages for a single country, and where I also can use the IPUMS data to calculate the average wages for skilled non-migrants.

[14]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.

The strategy for calculating the relative quality of skilled labor in the US and India is as follows. The post-migration wages of US native workers and Indian migrants is equal to the relative quality of the average US worker and the average Indian migrant.

$$\frac{w_{US,native}}{w_{US,migrant}} = \frac{Q_{s,US}}{Q_{s,migrant}}.$$

Furthermore, the relative wage of migrants in India and the average Indian skilled worker gives the relative quality of the migrants versus the average Indian skilled worker:

$$\frac{w_{Ind,migrant}}{w_{Ind}} = \frac{Q_{s,migrant}}{Q_{s,Ind}}.$$

Thus, we can calculate the relative quality of American and Indian skilled workers by multiplying the following two terms: the ratio of American average skilled wages to average post-migration wages, and the ratio of average pre-migration wages to average Indian skilled wages.

To calculate these two ratios, I convert all American wage data to 2005 dollar incomes, and all Indian data to 2005 rupee wages. I obtain the average salary for US skilled workers from the 2005 American Community Survey. I deflate this number with the average number of hours worked for the US reported in PWT 9.0 to obtain an hourly wage. To obtain post-migration dollar wages, I take the 2003 number reported in Hendricks and Schoellman (2017) and convert it to a 2005 number using US nominal GDP growth per worker.

For the Indian data, I use the 2004 Indian labor survey from IPUMS to obtain average weekly wages for skilled workers in India. I multiply this number by 48.6 [15] and divide it by the average number of hours worked in India for 2005 obtained from the PWT 9.0. I then convert it to 2005 figures by multiplying with Indian nominal GDP growth per worker between 2004 and 2005.

To convert the reported pre-migration wages to counterfactual 2005 rupee wages, I base my analysis on the reported pre-migration hourly wages from Hendricks and Schoellman (2017). In their paper, they report the last pre-migration wage per hour expressed in 2003 dollars. One challenge when analyzing India is that the sample is US workers who obtained permanent residence in the US in 2003, which means that many wages reflect Indian wages some years prior to 2003. Given the rapid growth of India, this might mean that they understate the counterfactual wage these workers would earn if employed in India. It is not possible to correct exactly for this since Hendricks and Schoellman (2017) do not report the average year which the pre-migration wages represent. To find the counterfactual wage in 2005 expressed in 2005 dollars, I multiply their reported number with Indian real GDP growth per worker between 2000 and 2003, as well as with Indian GDP growth in current dollars between 2003 and 2005. Lastly, I convert the 2005 dollars to rupees using the PWT 7.1. PPP exchange rate for 2005 (An earlier version of the PWT is used

[15] Using that India had 1 paid day of leave for every 20 days in 2004. Source: ILO Travail Legal Database. In addition, there are four paid national holidays. Number does not include local holidays.

since Hendricks and Schoellman (2017) used the PWT 7.1. to create dollar wages from Rupee wages).

Having constructed these variables, we now have both rupee wages and dollar wages for migrants and non-migrants. This is presented in Table 11. From this table, we see that Indian migrants have $124/49 \approx 2.51$ times higher wages than non-migrants. Thus, they are positively selected. At the same time, average American skilled wages are $31/20 \approx 1.55$ times higher than the wages the Indian migrants receive in the US. Combining these two numbers gives us a ratio in the quality of skilled labor of 3.9.

If we compare this with Table 10, we note that this finding is similar to the quality differences are similar to those found when I use a trade elasticity of $\sigma = 10$. This means, that for $\sigma = 10$, all skilled labor efficiency differences can be explained by a simple form of human capital differences. For lower values of σ, an explanation of skilled labor efficiency requires an additional mechanism: either occupational switching, complementarities between different skilled workers, or skill-biased technology differences.

	Ind (rupees/hour)	Ind ($/h nominal)	India ($/h PPP)	US ($/h)
Migrant	124.03	2.81	9.07	20.01
Nonmigrant	49.57	1.12	3.62	31.13

Table 11: Hourly wages for skilled migrants and non-migrants in India and the US

5 Comparison with 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.[16]

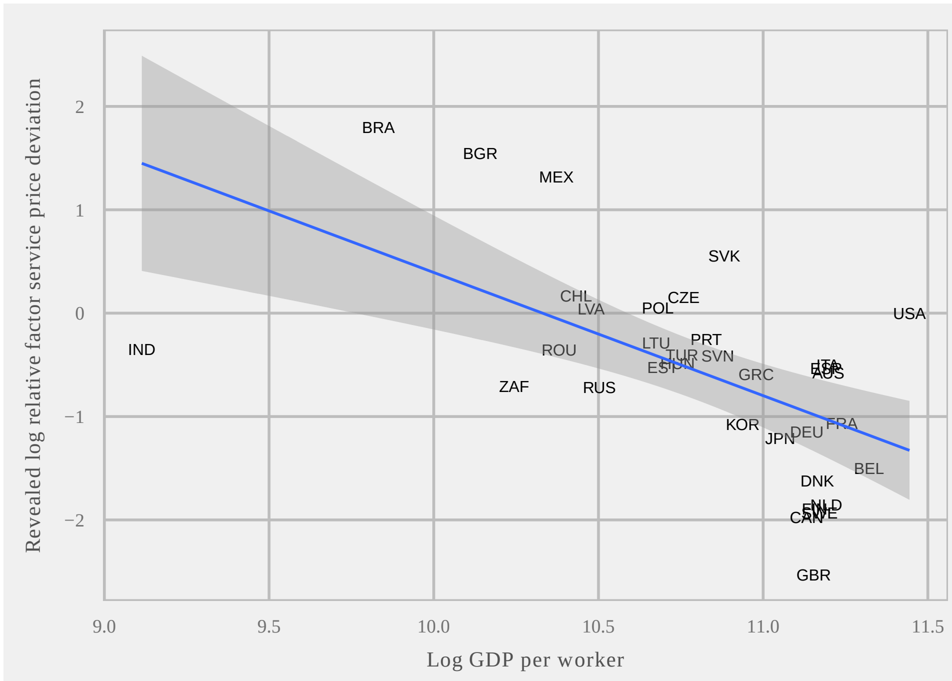
$$\log(c_i^k) = \delta_i + \mu_k + \sum_{f=2}^{F} \alpha_{US,f}^k \tilde{\beta}_{i,f}.$$

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

In Figures 2 and 3, 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

[16]In Appendix D.2, I derive this regression specification, and provide more details on all measurements.

Figure 2: Skilled price deviation estimates vs log GDP per worker using unit cost data



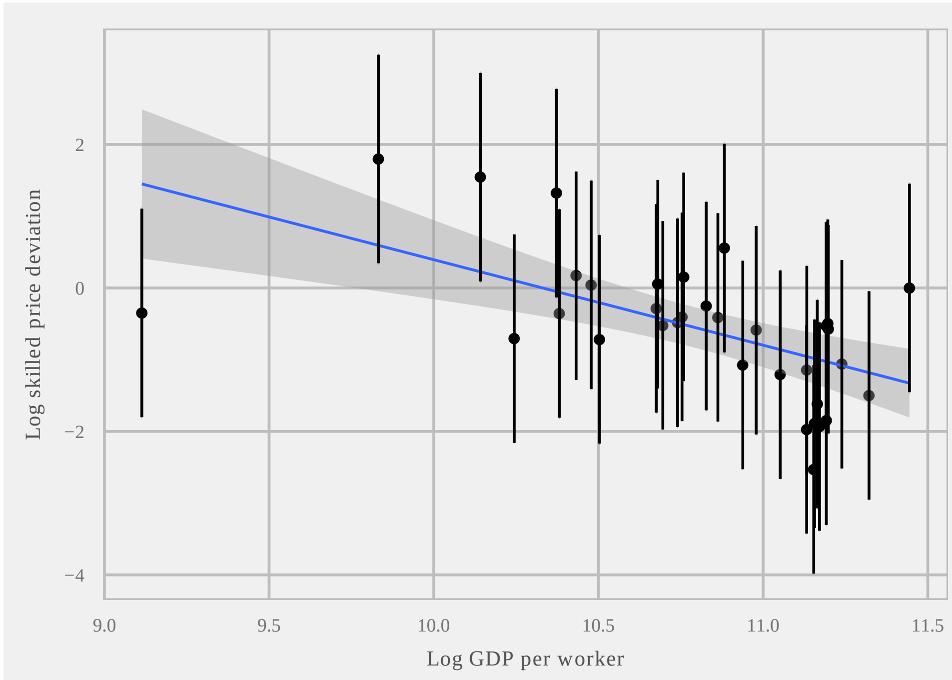
standard errors than the trade based estimates. This reflects the lower number of industries. However, just like the trade based estimates, they exhibit a strong negative correlation with log GDP per worker. The slope parameter of log relative skilled service prices on log GDP per worker is -1.19 using the unit cost data, and -0.8 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.

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-

Figure 3: Skilled price deviation estimates vs log GDP per worker using unit cost data



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 for the manufacturing sector, the required TFP differences fall from 4.3 to 2.0-3.0. 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 larger 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.

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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

$$U_j = \left(\sum_{i=1}^{I} \sum_{k=1}^{K} (a_j^k)^{1/\sigma} (q_{i,j}^k)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \qquad j = 1, \ldots, I;\ \sigma > 1 \tag{5}$$

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 (5) 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

$$c_i^k = C^k \left(r_{i,1}, \ldots, r_{i,F} \right) \tag{6}$$

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

$$P_{i,j}^{k} = c_i^k d_{i,j}. \tag{7}$$

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

$$Y_j = \sum_{f=1}^{F} r_{j,f} e_{j,f} \tag{8}$$

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 (6) and (7) respectively
4. Income is given by (8)
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 (6) for prices gives me

$$\log(x_{i,j}^k) = \delta_{i,j} + \mu_j^k - (\sigma - 1)\log(c_i^k) \tag{9}$$

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

$$c_i^k = C^k(r_{i,1}, \dots, r_{i,F}) \tag{10}$$

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

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

The offered price is

$$p_{i,j}^k(m) = \frac{c_i^k d_{i,j}}{z_i^k(m)} \tag{11}$$

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 (11). 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

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

I write

$$\Phi_j^k = \sum_i \left(c_i^k d_{i,j}\right)^{-\theta}. \tag{12}$$

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

$$x_{i,j}^k = \pi_{i,j}^k x_j^k = \frac{(c_i^k d_{i,j})^{-\theta}}{\Phi_j^k} x_j^k \tag{13}$$

Equation (13) 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 (13) 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 (4) 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, and traded intermediate inputs. 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 and traded intermediate inputs are traded relatively cheaply 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 (**??**). 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.

In my data, $\log(h_{trad})$ increases at approximately $0.15 - 0.2$ with GDP per capita. Thus, if

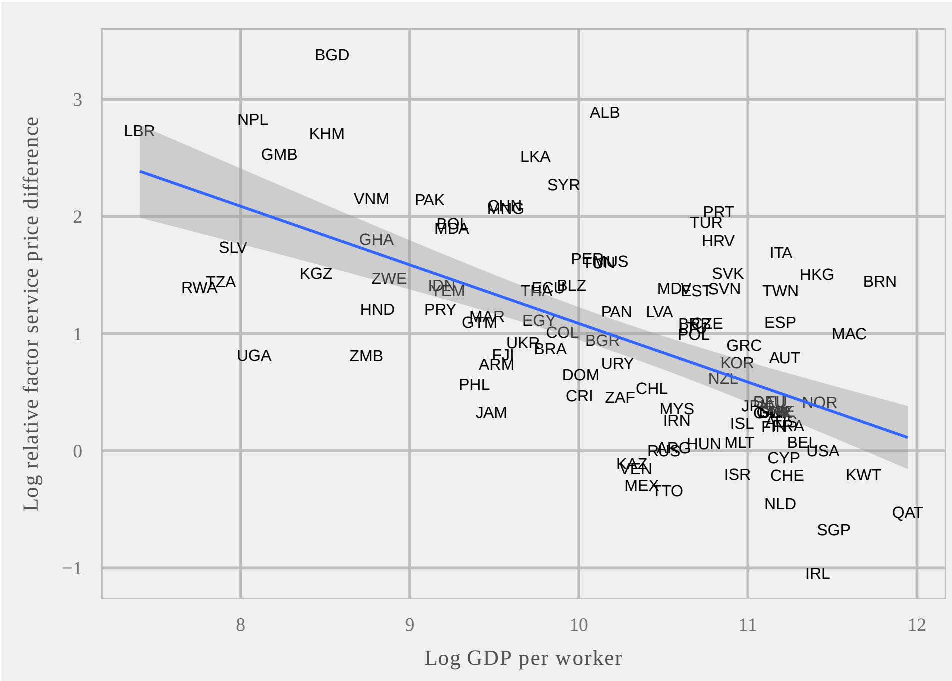

Figure 4: Log relative capital services prices and log GDP per worker

capital and intermediate inputs 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 4-6. 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 traded 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 across countries.

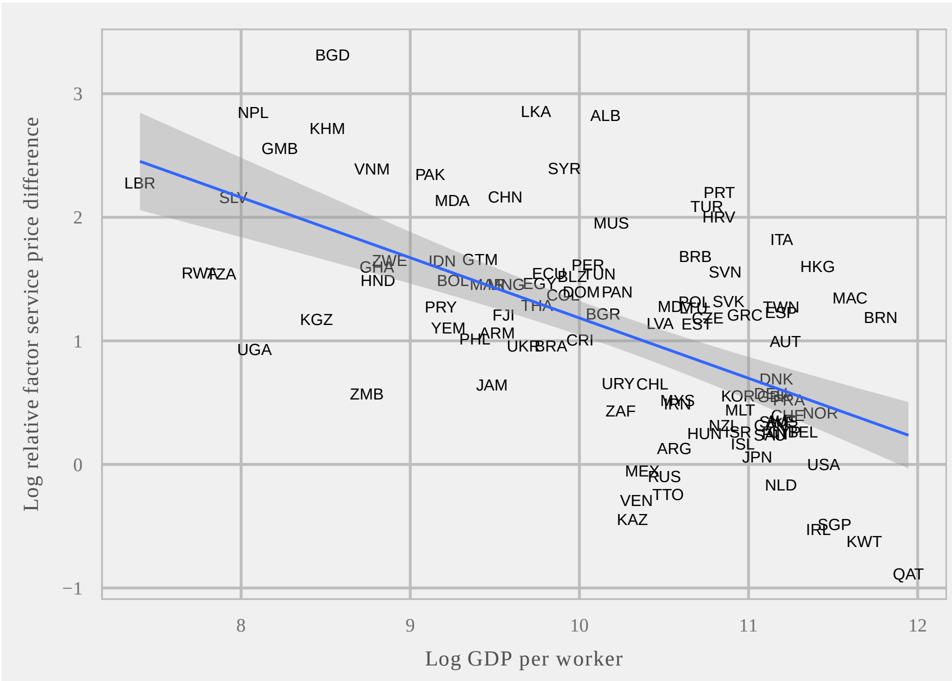

Figure 5: Log relative intermediate input services prices and log GDP per worker

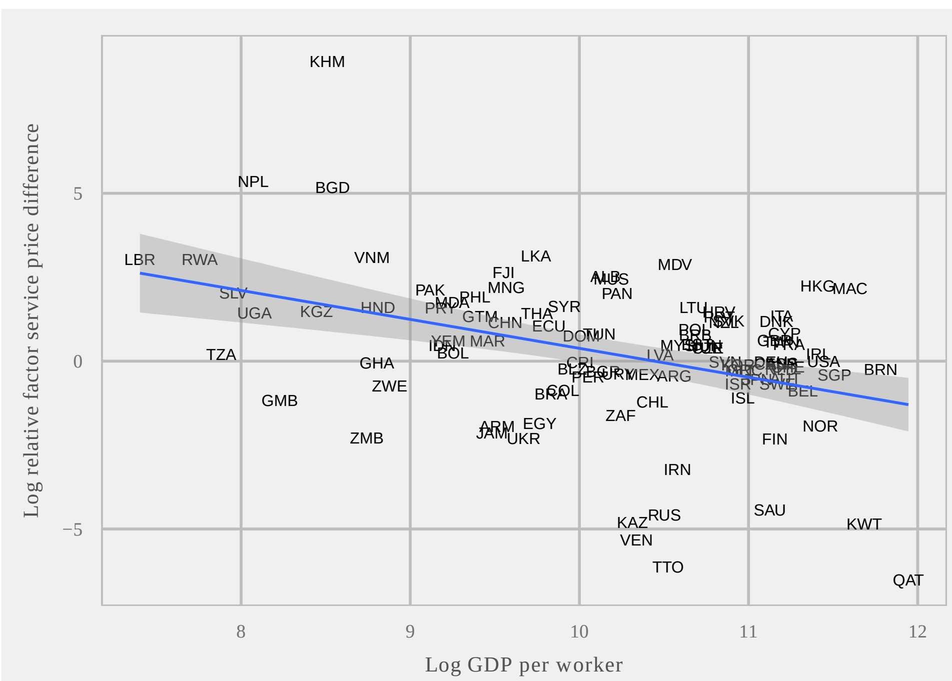

Figure 6: Log relative energy services prices and log GDP per worker

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.

To implement this approach, we need to separate the traded from the non-traded component of intermediate inputs. The intuition is that 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 calculate the share of traded intermediate inputs, I assume that manufacturing goods are traded.[17] I use the BEA information in the IO table to obtain information about capital, labor, and intermediate input shares in different industries, and the OES survey data to decompose the labor share into payments to skilled and unskilled workers.

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 $k = 1, \ldots, N_T + N_{NT}$, 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 $N_{NT} \times N_{NT}$ matrix giving the cost shares from nontraded inputs in the nontraded sector.

[17] 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.

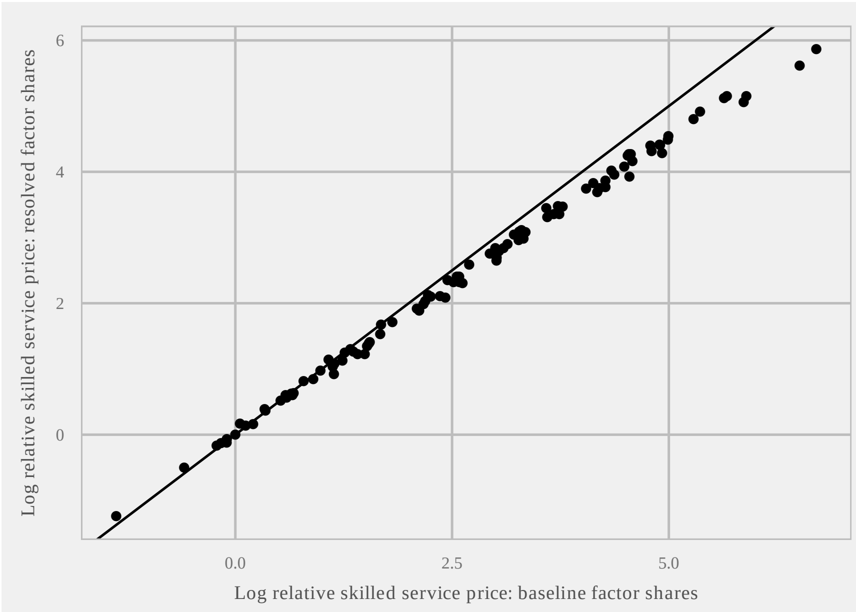

Figure 7: Comparison of estimated relative skilled service prices with different input measurements

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 7, 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.

The aggregate production function is

$$Y = AG(Q_uU, Q_sS, Q_kK).$$

Before proving the result, I will provide a formal statement of what equivalence means in this context. Assume that the true aggregate production function is

$$G(H^u, H^s, Q_kK)$$

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

$$\frac{w_s}{w_u} = \frac{Q_s}{Q_u}\frac{r_s}{r_u}, \tag{14}$$

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

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

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 $t_u = 1, \dots, N_u$, and a share s_{t_s} of the workforce performs skilled services of type t_s where $t_s = 1, \dots, N_s$. 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

$$\frac{w_{s,t_s}}{w_{u,t_u}} = \frac{G_s}{G_u}\frac{H^s_{t_s}Q_{s,t_s}}{H^u_{t_u}Q_{u,t_u}} = \frac{r_s}{r_u}\frac{H^s_{t_s}Q_{s,t_s}}{H^u_{t_u}Q_{u,t_u}},$$

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 (14) holds. First, I multiply both sides with $\tilde{s}_{t_s}$ and sum over $t_s = 1,\ldots,N_s$ to obtain

$$\frac{w_s}{w_{u,t_u}} = \frac{r_s}{r_u}\frac{Q^s}{H^u_{t_u}Q_{u,t_u}} \tag{15}$$

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 (14) by applying the same procedure to unskilled labor. I start with equation (15), 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. 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.[18]

[18]This modification is related to Krugman (1988) who shows that growing countries do not face **deteriorating**

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, the equilibrium conditions can be written as:

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

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 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 Proof of Theorem 1

I prove the theorem by construction. Define a function

$$\begin{aligned}
&G(\tilde{x}_1,\ldots,\tilde{x}_f) = \max_{\{\tilde{x}_f^k\}} H(F^1(\tilde{x}_1^1,\ldots,\tilde{x}_F^1),\ldots,F^K(\tilde{x}_1^K,\ldots,\tilde{x}_F^K)) \\
&s.t. \quad \sum_{k=1}^K \tilde{x}_f^k \le \tilde{x}_f \quad \forall f.
\end{aligned}$$

Furthermore, define

$$r_{i,f} = \frac{w_{i,f}}{Q_{i,f}}$$

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

If we write $\chi_i(\{x_{i,f}\}) = \{x_{i,f}^k : \sum_{k=1}^K x_{i,f}^k \leq x_{i,f}\}$ for the set of feasible factor allocation for economy i, we can see that the aggregate production function in country i is given by

$$\begin{aligned}
G_i(x_{i,1}, \ldots, x_{i,F}) &= \max_{\{x_{i,f}^k\} \in \chi_i(\{x_{i,f}\})} H(F_i^1(x_{i,1}^1, \ldots, x_{i,F}^1), \ldots, F_i^K(x_{i,1}^K, \ldots, x_{i,F}^K)) \\
&= \max_{\{x_{i,f}^k\} \in \chi_i(\{x_{i,f}\})} H(\tilde{A}_i F^1(Q_{i,1}x_{i,1}^1, \ldots, Q_{i,F}x_{i,F}^1), \ldots, \tilde{A}_i F_i(Q_{i,1}x_{i,1}^K, \ldots, Q_{i,F}x_{i,F}^K)) \\
&= \tilde{A}_i G(Q_{i,1}x_{i,1}, \ldots, Q_{i,F}x_{i,F}).
\end{aligned}$$

This proves that the aggregate production functions G_i can be written on a factor-augmenting form.

Furthermore, define the unit cost in sector k in country i as

$$\begin{aligned}
c_i^k &= \min_{\{x_f\}} \{\sum_f w_{i,f}x_f : F_i^k(x_1, \ldots, x_f) \geq 1\} \\
&= \min_{\{x_f\}} \{\sum_f w_{i,f}x_f : \tilde{A}_i F^k(Q_{i,1}x_1, \ldots, Q_{i,f}x_f) \geq 1\} \\
&= \frac{\min_{\{x_f\}} \{\sum_f r_{i,f}Q_{i,f}x_f : F^k(Q_{i,1}x_1, \ldots, Q_{i,f}x_f) \geq 1\}}{\tilde{A}_i} \\
&= \frac{c^k(r_{i,1}, \ldots, r_{i,F}}{\tilde{A}_i}.
\end{aligned}$$

Thus, the set $r_{i,f}$ governs relative unit costs across sectors. The assertion that $\frac{w_{i,f}}{w_{i,f'}} = \frac{Q_{i,f}}{Q_{i,f'}} \frac{r_{i,f}}{r_{i,f'}}$ is true by assumption. The assertion that

$$\frac{G_f}{G_{f'}} = \frac{r_{i,f}}{r_{i,f'}}$$

follows from standard theory of constrained optimization.

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 8. 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 9 compares the results from an education based and occupation based definition of the skill share. Figure 9 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

Figure 8: 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

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.

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.

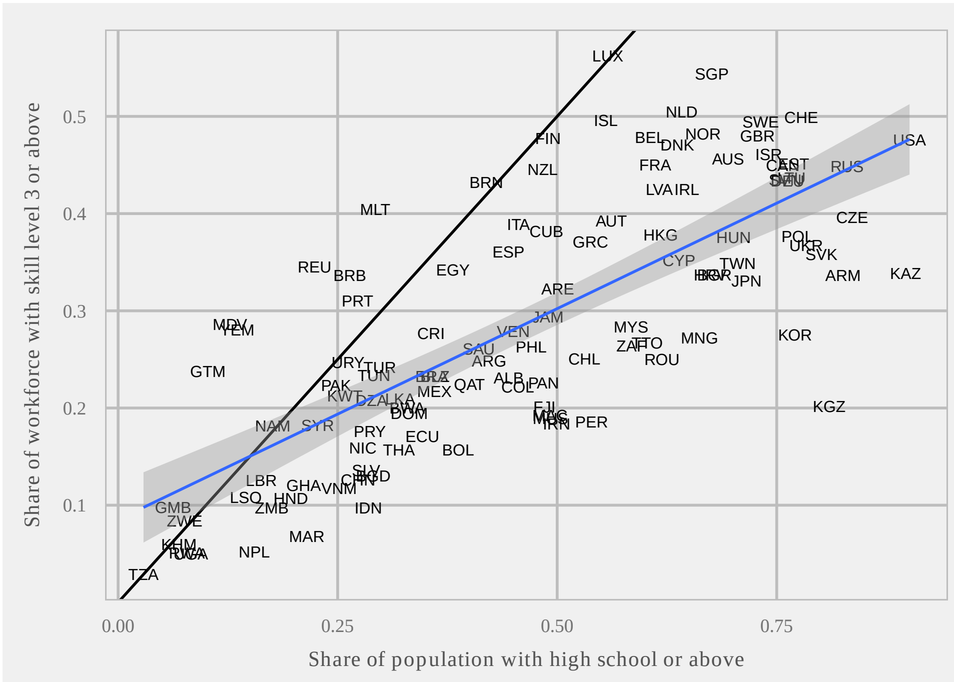

Figure 9: High school and above and share of skilled occupations

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 (4) 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 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.[19]

In Figures 2 and 3, 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.3 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.

E Appendix: Concordance construction

To generate concordances and map data across coding systems, I create a general mathematical framework to treat the problem. Here, describe how the general system works, and then I show how I use it to convert our particular data.

The basic building block of our concordance system is a many-to-many concordance between coding systems A and B where I have weights on both A and B. I call such concordances two-weighted concordances. An example of such a concordance is provided in Table 12.

[19] 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 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.

Table 12: Example concordance table

A	B	A_w	B_w
1	a	10	70
2	b	20	50
2	c	20	100
3	c	15	40
4	d	5	70
5	d	25	70
6	e	30	90

In Table 12, note that each code in system A can be converted to multiple B codes (in this example, code 2 in System A maps to both code b and c in System B). The converse is also true: both code 4 and 5 map to code e. The weights code how important the respective industries are. This could, for example, be the total value of shipments, total trade value, etc. Notice that the weights are both on A and B, and that they are constant whenever they stand for the same industry.

I can define this mathematically as there being two sets A,B with measures w_A, w_B giving the mass on each code, and a concordance being a correspondence

$$\phi : A \rightrightarrows B.$$

I will write results in terms of this mathematical definition, but also in terms of examples to show the working of the system.

I will go through three operations relating to two-weighted concordances:

1. How to transform quantity variables such as total industry sales using a two-weighted concordance

2. How to transform property variables such as capital share using a two-weighted concordance

3. How to create a two-weighted concordance using an unweighted concordance and a weighting scheme for one of the variables (e.g. when I want to create a two-weighted concordance between HS and SITC and only have total trade in HS codes).

F Transform quantity variables using two-weighted concordances

Starting with quantity variables, suppose that I have export values denoted in industry code A. I then want to allocate it across different codes in industry code B given a weighting scheme on B. In this case, for each element $a \in A$, I allocate the export values in industry a across industries

$b \in B$ in proportion to their weights w_b. The quantity attributed to element $b \in B$ is then the sum of the contributions from all elements in A to b.

I can write this in terms of the mathematical representation Φ as well, together with the weights μ_A and μ_B. If

$$f_A : A \to \mathbb{R}$$

is an arbitrary quantity measure on A I convert it to B by

$$f_B(b) = \sum_{a \in \Phi^{-1}(b)} f_A(a) \times \frac{\mu_B(b)}{\sum_{b' \in \Phi(a)} \mu_B(b')}.$$

G Transform property variables using two-weighted concordances

The situation is different when I have so-called property variables, for example capital share, skill share or other industry-level properties. The difference can be illustrated with an example.

In the previous part, I considered the problem of mapping trade data from A to B. Then, the reasonable thing is to split it up the value a across $b \in \Phi(a)$ according to the weights w_b. However, suppose that I want to map the capital share from a to b. Then, we should not split up the capital share across $b \in \Phi(a)$. If b and b' have the same pre-image a, they should have the same capital share as a.

Thus, property variables translate across coding systems in a fundamentally different way from quantity variables. I define the transformation scheme for property variables by saying that for each code $b \in B$ in the target system, I define its property as a weighted average of the properties that its pre-images $a \in A$, where I use the weights on A as a weighting scheme. For example, in our example concordance, I would attribute c a property which is the weighted average of 2,3 in System A, using the measures $\mu_A(\{2\}) = 20$ and $\mu_A(\{3\}) = 15$ as weights.

More formally, if I have a property measure

$$g_A : A \to \mathbb{R}$$

defined on A, then I translate it to B using ϕ by the equation

$$g_B(b) = \frac{\sum_{a \in \phi^{-1}(y)} g_A(a)\mu_A(a)}{\sum_{a \in \phi^{-1}(b)} \mu_A(a)}.$$

G.1 Construct a two-side weighted concordance from a one-sided weighted concordance

Above I defined how you translate between different coordinate systems if you have a two-sided weighted concordance. However, sometimes I only have a one-sided concordance. For example, if

I have total trade data in HS 2007 six-digit and want to create a concordance between HS 2007 6-digit and NAICS 2007 it might be that I do not have data to create a natural weighting scheme for the NAICS 2007 coding scheme.

For this case, I have a procedure to create a two-sided weighted concordance from a one-sided weighted concordance. It is quite similar to the quantity transformation above. Suppose that I have a concordance ϕ and a measure μ_A on A and want to create a measure μ_B on B. Then I define the measure on B as.

$$\mu_B(b) = \sum_{x \in \phi^{-1}(b)} \frac{\mu_A(a)}{|\phi^{-1}(a)|}.$$

That is, I split the weights on $a \in A$ equally on all $b \in B$ to which a maps.