Skilled Labor Productivity and Cross-country Income Differences

By Lutz Hendricks and Todd Schoellman*

This paper revisits the question of how allowing for imperfect substitution among workers with different skill levels affects the results of development accounting. We consider a range of models that nest the approaches in the literature and calibrate them to a common set of moments, including particularly evidence on the wage gains of migrants. We obtain two main results. First, human capital accounts for between one-half and three-fourths of cross-country income gaps. Second, human capital accounts for only modest variation in the relative productivity of skilled versus unskilled labor.
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A central objective of economics is to understand the large cross-country differences in output per worker. Development accounting improves our understanding by decomposing these differences into the contributions of factor inputs and total factor productivity. Its objective is to shed light on the proximate sources of cross-country income differences, which can be a useful guide for theory and policy-makers.

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Most of the early development accounting literature focuses on the case where workers with different skill levels are perfect substitutes.[1] This assumption is at odds with an extensive literature that documents large movements in relative wages and attributes them to shifts in the relative supply of and demand for skilled labor (Katz and Murphy, 1992; Goldin and Katz, 2008). Several recent papers have begun to incorporate imperfect substitution among labor types into development accounting, with mixed results. There is particular uncertainty about how imperfect substitution affects the implied importance of human capital for development accounting. Among three recent papers, Caselli and Ciccone (2013) finds that it lowers it, Jones (2014) that it substantially raises it, and Hendricks and Schoellman (2018) that it does not make much difference.[2]

This paper seeks to bring additional clarity to this debate. We consider models that allow for multiple factors that affect the relative supply of or demand for skilled labor, including those proposed in the previous literature. We calibrate all these models to the same data, including particularly the evidence on the wage gains at migration from Hendricks and Schoellman (2018). Migrants provide useful evidence because they carry their human capital to a new country with different labor demand. Their wages can be used to help disentangle cross-country variation in labor supply and labor demand. Across a variety of models, we find a tight range of estimates for the importance of human capital for development accounting.

Our benchmark model allows firms in each country to choose the efficiency of skilled and unskilled labor from a technology frontier, as in Caselli and Coleman (2006).[3] Firms respond optimally to a greater quantity of skilled labor (a higher

[1] Bils and Klenow (2000) pioneered the necessary framework, which was first adopted for development accounting purposes by Hall and Jones (1999). See also Caselli (2005), Hsieh and Klenow (2010) , and Caselli (2016) for surveys of the literature.

[2] A recent exchange between Caselli and Ciccone (2019) and Jones (2019) helps clarify some of the issues at stake but does not reach agreement on the conclusion. This work complements a parallel literature that develops quantitative theories of human capital formation, including Erosa, Koreshkova and Restuccia (2010), Córdoba and Ripoll (2013), and Cubas, Ravikumar and Ventura (2016).

[3] We show in an extension that the model equally well accommodates directed technical change as

share of skilled workers or relatively more human capital per skilled worker) by choosing more skill-biased technologies, as in Okoye (2016). Our first proposition shows that this model is analytically equivalent to one where the skill bias of technology is exogenous and common to all countries, but the elasticity of substitution is larger. We call this larger elasticity the long-run elasticity of substitution; it mixes the traditional (short-run) elasticity of substitution with the curvature of the technology frontier.

This proposition has two important implications. First, it implies that it may be worthwhile to consider larger values of the elasticity of substitution in contexts where technological response to skill endowments is plausible. Recent work estimates this long-run elasticity of substitution and provides evidence that it is closer to 4–6 (Hendricks and Schoellman, 2018; Bils, Kaymak and Wu, 2020). Second, existing work that takes models with imperfect substitution among labor types to the data take one of two approaches. Some consider a wide range of values for the elasticity of substitution (Jones, 2014). Others fix attention on the conventional (short-run) elasticity of substitution but allow cross-country variation in the skill bias of technology (Caselli and Coleman, 2006). The proposition establishes that the approaches are analytically equivalent in this model.

We then develop a decomposition result in the spirit of one proposed by Jones (2014) to show that the role of human capital in development accounting can be broken into two terms. The first term captures the effect that would arise in a model with perfect substitution among labor types; it depends only on the difference in human capital of unskilled workers across countries. The second term captures the effect that is special to models with imperfect substitution. It in turn depends on the elasticity of substitution among labor types and how much the relative supply of skilled labor varies across countries.

We calibrate the model to fit standard cross-country data plus the new evidence on

in Acemoglu (2007). For additional evidence on skill-biased technical change see also Acemoglu (1998), Acemoglu and Ventura (2002), Gancia and Zilibotti (2009), and Jerzmanowski and Tamura (2019).

wage gains at migration for workers with different skill levels from Hendricks and Schoellman (2018). We confirm our previous finding that human capital accounts for roughly 60 percent of cross-country income differences. Most of this result is due to the first term in the Jones (2014) decomposition. The previous literature has largely abstracted from this effect due to a lack of data. Empirically, the wage gains for migrants from poor countries are small (relative to the total gap in GDP per worker). These small gains point to a small role for country-specific factors and hence a large role for human capital gaps across countries. This effect does not depend on imperfect substitution among worker types.

The second term has been much more controversial in the literature. The reason is that there are large differences in the share of skilled workers across countries, but small or no differences in the skilled wage premium (Barro and Lee, 2013; Banerjee and Duflo, 2005). Given a framework with imperfect substitution among labor types, it follows that rich countries must have much higher skilled labor productivity.[4] The disagreement has been whether this productivity is the result of much higher human capital of skilled workers or much more skill-biased technology; the implications are starkly different, particularly for development accounting.

Our resolution of this debate builds on the relative wage gains of skilled versus unskilled migrants. Intuitively, if abundant skilled labor in rich countries is balanced by skill-biased technologies, then skilled migrants from poor countries would benefit from these technologies and experience wage gains. On the other hand, if it is balanced by high human capital per rich country skilled worker, then skilled migrants would not benefit and so would experience wage losses. Empirically, skilled migrants experience wage gains that are modestly smaller than those of unskilled migrants. This finding suggests that variation in the relative productivity of skilled labor is mostly due to skill bias of technology. This approach and

[4] Malmberg (2019) provides independent evidence in favor of cross-country variation in skilled labor productivity using the skill intensity of countries' manufacturing exports and imports.

result closely follows prior work by Okoye (2016) and Rossi (2019).[5] Returning to our analytical result, we can also say that this finding is equivalent to allowing for a higher long-run elasticity of substitution, which implies that the imperfect substitution term is less important for development accounting results.

Most of our results extend to alternative versions of the model. We consider models where the skill bias of technology is taken as exogenous but allowed to vary by countries. Our equivalence result no longer applies in these models. We also face the well-known issue that it matters which country's technology we choose to evaluate the importance of human capital for development accounting. We provide results using different countries' technologies and for a range of values of the elasticity of substitution. As long as we discipline the results with the same moments of wage gains at migration, we arrive at similar results. We also add to the literature by considering for the first time the role of capital-skill complementarity, an additional shifter of the demand for skilled labor (Krusell et al., 2000). Once again, we find that the model yields similar results when calibrated to the same moments.

Our decomposition result holds in all of our models and so provides a useful way to summarize results across models. We consistently find that the first "perfect substitutes" term is large, accounting for at least 45 percent of income differences. This finding obtains because the wage gains of migrants are consistently small relative to the difference in GDP per worker. We find that the second "imperfect substitutes" term is generally small but more variable, ranging from 0 to 20 percent of income differences. This finding arises because the wage gains of unskilled migrants are modestly larger than those of skilled migrants, which implies that most of the cross-country differences in skilled labor productivity are attributable to skill bias of technology. Given the central role the wage gains of migrants play in disciplining all these models, we conclude by providing robustness checks, with

[5] Caselli and Ciccone (2019) make the opposite point: if skilled labor productivity differences are due to human capital, then skilled migrants from rich to poor countries should experience large wage gains.

a particular focus on the impact of allowing for plausible differences in wage gains at migration.

I. Endogenous Technology Model

We perform development accounting in an environment that allows for relative wages to be affected by labor supply factors (relative labor quantities and qualities) and labor demand factors (relative skill bias, relative complementarity with other inputs).

A. *Model Specification*

The endogenous technology model combines the production function and human capital structure of Jones (2014) with the technology frontier of Caselli and Coleman (2006). There are two countries, indexed by $c \in \{p, r\}$ (poor and rich). Output per worker Y_c is produced from per worker physical capital K_c and labor L_c according to the production function

$$Y_c = K_c^{\alpha} \left(z_c L_c\right)^{1-\alpha} \tag{1}$$

where z_c denotes total factor productivity. Labor input per worker is a CES aggregator of unskilled ($j = u$) and skilled ($j = s$) labor inputs

$$L_c = \left[\sum_{j\in\{u,s\}} \left(\theta_{j,c} L_{j,c}\right)^{\rho}\right]^{1/\rho}. \tag{2}$$

The elasticity of substitution between skilled and unskilled labor is $\sigma = 1/\left(1-\rho\right) > 1$, so that $0 < \rho < 1$. Labor inputs $L_{j,c} = h_{j,c} N_{j,c}$ are the product of labor qualities $h_{j,c}$ and quantities $N_{j,c}$. The supplies of $h_{j,c}$ and $N_{j,c}$ in each country are taken as exogenous. The skill weights $\theta_{j,c}$ are constrained by a technology frontier, similar to Caselli and Coleman (2006) or Acemoglu (2007), given by

$$\left[\sum_j (\kappa_j \theta_{j,c})^\omega\right]^{1/\omega} \leq B_c \tag{3}$$

with $\omega > 0$. The shape parameters κ_j are exogenous and common across countries. As in Caselli and Coleman (2006), we assume that

$$\omega - \rho - \omega\rho > 0 \tag{4}$$

This condition ensures that firms choose an interior point on the technology frontier.

In line with the development accounting literature, we assume that the economy is in steady state with an interest rate that is equal to the discount rate of the infinitely lived representative agent (e.g., Hsieh and Klenow 2010). This fixes the rental price of capital q_c and therefore K_c/Y_c. The rental prices of labor inputs, $p_{j,c}$, are determined by labor market clearing. The representative firm solves

$$\max_{K_c, L_{j,c}, \theta_{j,c}} Y_c - q_c K_c - \sum_j p_{j,c} L_{j,c} \tag{5}$$

subject to (1), (2), and (3), taking factor prices as given.

Note that observable wage rates per hour are given by $w_{j,c} = h_{j,c} p_{j,c}$. Hence, the total earnings of skill j workers are given by $W_{j,c} = p_{j,c} L_{j,c} = w_{j,c} N_{j,c}$. The values of $p_{j,c}$ are not directly observable in the data.

Our setup nests the model of Caselli and Coleman (2006) as a special case when $h_{j,c} = 1$. It nests the model of Jones (2014) when the choice of skill bias is removed and $\theta_{j,c} = 1$.

B. Development Accounting

We discuss how to perform development accounting when the skill bias of technology is endogenous. As is standard in the literature, we start from

$$Y_c = z_c \left(K_c/Y_c\right)^{\alpha/(1-\alpha)} L_c \tag{6}$$

and decompose the output per worker gap into the contributions of TFP, physical capital, and (jointly) labor inputs and skill bias according to

$$\underbrace{\Delta \ln (Y)}_{\text{output gap}} = \underbrace{\Delta \ln (z)}_{\text{TFP}} + \underbrace{\Delta \ln \left((K/Y)^{\alpha/(1-\alpha)} \right)}_{\text{physical capital}} + \underbrace{\Delta \ln (L)}_{\text{labor + skill bias}} \tag{7}$$

where we use $\Delta \ln$ to denote the log gap between the rich and the poor country; e.g., $\Delta \ln (Y) \equiv \ln (Y_r) - \ln (Y_p)$. The share of the output gap accounted for by each input is given by

$$1 = \underbrace{\frac{\Delta \ln (z)}{\Delta \ln (Y)}}_{\text{share}_z} + \underbrace{\frac{\Delta \ln \left((K/Y)^{\alpha/(1-\alpha)} \right)}{\Delta \ln (Y)}}_{\text{share}_K} + \underbrace{\frac{\Delta \ln (L)}{\Delta \ln (Y)}}_{\text{share}_L} \tag{8}$$

The literature typically defines the contribution of each input to cross-country output gaps via a counterfactual experiment. For example, the contribution of human capital is defined as the change in steady state output when human capital is increased from the poor country's to the rich country's level. To the extent that other inputs respond endogenously, their effect is counted as part of human capital's contribution. In particular, the counterfactual holds the capital-output ratio constant. This captures the induced changes in the capital stock when the saving rate is unchanged (see Hsieh and Klenow, 2010).

In line with this approach, the endogenous technology model counts the effects of induced changes in the skill bias of technology as part of the contribution of labor inputs, measured by $share_L$. Alternatively, $share_L$ could be defined as the change in steady state output, holding skill bias fixed. The exogenous skill bias model considers this approach in Section III. More generally, the skill bias of technology could be partially an endogenous response to relative labor supply and partially a response to other factors or even purely exogenous. The endogenous and the exogenous technology models bound the development accounting results for such cases.

C. Reduced Form Labor Aggregator

One challenge for development accounting is the identification of the two elasticities that govern the substitution between skilled and unskilled labor (ρ and ω). Our first result shows that $share_L$ can be estimated without separately identifying both parameters.

PROPOSITION 1: *Solving out the firm's optimal skill bias choices yields the reduced form labor aggregator*

$$L_c = B_c \left[\sum_j \left(\kappa_j^{-1} L_{j,c} \right)^{\Psi} \right]^{1/\Psi} \tag{9}$$

with an elasticity of substitution governed by

$$\Psi = \frac{\omega \rho}{\omega - \rho} > \rho \tag{10}$$

PROOF:

Section B.B2

Proposition 1 establishes that allowing for technology choice is equivalent to increasing the elasticity of substitution while holding the skill bias of technology fixed. The reduced form skill bias parameters $\left(\kappa_j^{-1}\right)$ are common across countries and governed by the technology frontier. Variation in the level of the frontier B_c has the same effect as variation in z_c.

In other words, we are back in the world of Jones (2014) with one crucial difference: the "short-run" elasticity of substitution of the original labor aggregator $1/\left(1-\rho\right)$ no longer matters by itself. It is replaced by a higher, "long-run" elasticity $1/\left(1-\Psi\right)$ that combines the curvatures of the labor aggregator and the technology frontier. The long-run elasticity reflects two equilibrium responses to an increase in skilled labor abundance $L_{s,c}/L_{u,c}$. The first (standard) response is that the lower skilled wage premium induces firms to substitute along the isoquant of the original CES production technology (2). The second effect is that firms choose a more skill-biased technology along the frontier (3).[6] Not having to separately identify ρ and ω greatly simplifies the calibration.

D. *Closed Form Solution*

Before we calibrate the model, we derive a closed form solution for the contribution of labor inputs to cross-country output gaps, $share_L$.

PROPOSITION 2: *The share of output gaps due to labor inputs is given by*

$$share_L = \underbrace{1 - \frac{\ln\left(\frac{p_{u,r}}{p_{u,p}}\right)}{\Delta \ln\left(Y\right)}}_{perfect\ substitutes} + \underbrace{\left(\frac{1}{\Psi} - 1\right)\frac{\ln\left(\frac{W_r/W_{u,r}}{W_p/W_{u,p}}\right)}{\Delta \ln\left(Y\right)}}_{imperfect\ substitutes} \tag{11}$$

where $W_{j,c}$ denotes the labor earnings of skill j in country c and $W_c \equiv \sum_j W_{j,c}$ denotes total labor income in country c. The long-run elasticity parameter Ψ

[6]The higher long-run elasticity of substitution may also result from reallocation across sectors. As worker skills increase, skill intensive sectors may expand, effectively providing an additional margin of substitution.

satisfies

$$\Psi = \ln\left(\frac{W_{s,r}/W_{u,r}}{W_{s,p}/W_{u,p}}\right) / \ln\left(\frac{L_{s,r}/L_{u,r}}{L_{s,p}/L_{u,p}}\right) \tag{12}$$

PROOF:

Section B.B3

The solution for $share_L$ consists of two terms. The perfect substitutes term is the contribution of labor inputs to output gaps with perfect substitution of skills. Intuitively, the skill price gap $\frac{p_{u,r}}{p_{u,p}}$ captures the importance of changing country-specific factors (capital, TFP) for a worker's wages. If the skill price gaps are as large as GDP per worker gaps, then country-specific factors account for all of income differences. If not, the remainder of GDP per worker gaps is attributable to the gaps in average human capital between countries. For example, if skill prices do not differ across countries, then we would infer that country-specific factors are irrelevant and human capital accounts for all of cross-country income differences.[7]

With imperfect skill substitution, the role of human capital is magnified when the rich country is skill abundant, so that $h_{s,r}/h_{u,r} > h_{s,p}/h_{u,p}$. This is captured by the imperfect substitutes term in (11).[8] As in Jones (2014), we can sign this term to be positive, meaning that allowing for imperfect substitution and technology choice expands the role of human capital in development accounting. Its magnitude depends on the elasticity of substitution parameter Ψ and the rich country's relative abundance of skilled labor, captured by the poor-to-rich country gap in the unskilled labor income share, $\ln\left(\frac{W_r/W_{u,r}}{W_p/W_{u,p}}\right)$.

[7] Formally, when skills are perfect substitutes and labor shares do not differ across countries, the wage gap $\Delta \ln(w)$ equals the output gap $\Delta \ln(Y)$. Since $w = ph$, we have $\Delta \ln(h) = \Delta \ln(w) - \Delta \ln(p) = \Delta \ln(Y) - \Delta \ln(p)$. Therefore, $1 - \Delta \ln(p)/\Delta \ln(Y)$ is the contribution of labor inputs to output gaps.

[8] As $\frac{h_{s,r}/h_{u,r}}{h_{s,p}/h_{u,p}} \to 1$, the imperfect substitutes term vanishes because $\frac{L_{s,r}/L_{u,r}}{L_{s,p}/L_{u,p}} \to \frac{N_{s,r}/N_{u,r}}{N_{s,p}/N_{u,p}} = \frac{W_{s,r}/W_{u,r}}{W_{s,p}/W_{u,p}}$, so that $(1/\Psi - 1) \to 0$.

We argue in section Section II.A that all of the terms in equation (11) and equation (12) can be estimated from data. This allows us to obtain precise intuition about how $share_L$ depends on data moments. Moreover, since the same solution applies to the model of Jones (2014) (except that the substitution elasticity is governed by ρ instead of Ψ), we gain insight into how his development accounting results differ from ours.

II. Quantitative Results

This section presents the development accounting implications of the endogenous technology model, calibrated to match data moments for output gaps, labor income shares and employment by skill, and migrant wage gains.

A. *Data and Measurement*

According to Proposition 2, the value of $share_L$ depends on four terms: cross-country gaps in output per worker Y_r/Y_p and skill prices $p_{j,r}/p_{j,p}$, wage bill ratios $W_{s,c}/W_{u,c}$, and the long-run elasticity of substitution Ψ. The elasticity can in turn be calibrated to match how much wage bill ratios covary with labor inputs (equation (12)).

Several of these objects are familiar from the literature and admit standard measurement. For the remaining objects that are less familiar (skill prices, labor inputs, and labor qualities) we draw on evidence from Hendricks and Schoellman (2018). A number of additional model parameters are normalized by choice of units. Specifically, we normalize $B_c = 1$ and $\kappa_u = 1$ by choosing z_c.[9] We also normalize $\kappa_s = 1$ by choosing skilled labor quality units.

Following Hendricks and Schoellman (2018), the rich country is the U.S. while the poor country is the median of 63 countries with $Y_c/Y_r < 1/4$. Output and

[9]This normalization of B_c is removed in Appendix D where firms are allowed to invest in extending the technology frontier (increasing B_c, as in Acemoglu 2007). We show that the development accounting results remain unchanged if the costs of investing in B_c scale appropriately with output, so that the aggregate production function features constant returns to scale.

capital per worker are taken from the Penn World Tables 7.1 (Feenstra, Inklaar and Timmer, 2015). The capital share is set to 0.33. Table 1 summarizes these data moments.

Table 1—: Data Moments Independent of Skill Cutoff

	Y	K/Y	Capital share
Rich	1.00	3.18	0.33
Poor	0.09	2.66	0.33
Ratio	10.70	1.19	1.00

The remaining data moments require a definition of skilled and unskilled workers. Following the literature, we consider different lower bounds on the set of skilled workers: some secondary schooling (SHS), secondary degree (HSG), and some college (SC). Table 2 shows the data moments for each skill cutoff.

Labor quantities $N_{j,c}$ are constructed as follows. From Barro and Lee (2013) we obtain the employment shares $N_{\iota,c}^{BL}$ of workers in seven schooling categories ι (no school, some primary, primary completed, some secondary, secondary completed, some tertiary, tertiary completed). Within each skill group (skilled or unskilled) we assume that workers are perfect substitutes, so that $N_{j,c} = \sum_{\iota \in j} \tilde{\phi}_\iota N_{\iota,c}^{BL}$. Lemma 1 of Jones (2014) implies that this assumption is without loss of generality. We further assume that $\tilde{\phi}_\iota \propto e^{\phi t_\iota}$ $\forall \iota \in j$ where t_ι denotes the durations of schooling category ι, which we set to $t_\iota = [0, 3, 6, 9, 12, 14, 16]$.

If workers are paid their marginal products, observable wages measure the relative efficiencies $\tilde{\phi}_\iota$ of workers within a skill group j. Based on the evidence collected by Banerjee and Duflo (2005), Caselli (2016), and Jedwab et al. (2020) we assume a Mincer return of $\phi = 0.1$ for all countries but explore alternatives in the robustness analysis of section Section II.D. Finally, we choose units of skilled and unskilled labor qualities such that $N_{u,r} = N_{s,r} = 1/2$. As expected, the first panel of

Table 2—: Data Moments

	Skill Cutoff		
	SHS	HSG	SC
Skilled/unskilled labor quantity, N_s/N_u			
rich	1.00	1.00	1.00
poor	0.04	0.21	0.22
rich/poor	27.45	4.86	4.45
Skilled/unskilled wage bill, W_s/W_u			
rich	71.11	3.74	1.43
poor	2.59	0.77	0.32
rich/poor	27.45	4.86	4.45
Migrant wage gain, π			
unskilled	3.71	3.46	2.98
skilled	2.29	2.21	2.08
unskilled/skilled	1.62	1.57	1.43

Table 2 shows that skilled labor is abundant in rich countries.

Given the assumed Mincerian earnings function, wage bill ratios are given by

$$\frac{W_{s,c}}{W_{u,c}} = \frac{\sum_{\iota \in s} e^{\phi t_\iota} N_{\iota,c}^{BL}}{\sum_{\iota \in u} e^{\phi t_\iota} N_{\iota,c}^{BL}} \tag{13}$$

These are shown in the second panel of Table 2. With equal Mincer returns across countries, relative earnings and relative labor quantities vary across countries by the same amount: $\frac{W_{s,r}/W_{u,r}}{W_{s,p}/W_{u,p}} = \frac{N_{s,r}/N_{u,r}}{N_{s,p}/N_{u,p}}$.

We are left with two objects for which the literature offers no standard measurement approach: skill prices $p_{j,c}$ and labor qualities $h_{j,c}$. We argue that migrant wage gains are informative about both. Conceptually, the argument is that since migrants have the same human capital in their birth country and the United States, the change in their labor earnings reflects gaps in the market price for their skills. Formally, denote by π_j the wage gains of migrants of skill level j who migrate from the poor to the rich country. Assuming that each worker supplies the same human capital in each country, the wage gain equals the ratio of skill prices, $\pi_j = p_{j,r}/p_{j,p}$. Since observed wages are given by $w_{j,c} = p_{j,c}h_{j,c}$, labor quality gaps obey

$$\Delta \ln (h_j) = \Delta \ln (w_j) - \Delta \ln (p_j) \tag{14}$$

Finally, labor input per worker may be calculated as $L_{j,c} = h_{j,c}N_{j,c}$.

For evidence on migrant wage gains, we draw on previous work where we use three data sets with data on pre- and post-migration wages of different groups of immigrants to the U.S. (Hendricks and Schoellman, 2018). We document a number of facts about wage gains, particularly for migrants from poor countries (GDP per worker less than one-fourth of the U.S.). Table 2 shows two of these facts that are central for our analysis.

First, the average wage gain is roughly a factor of three, as compared to an average GDP per worker gap of 10.7. Second, wage gains vary systematically and negatively with education. College educated migrants have wage gains of roughly a factor of two, while migrants without high school degrees have gains of roughly a factor of four. This gap is qualitatively consistent with imperfect substitution across skill groups: through the lens of this framework, more educated workers gain less because they move from a country where they are relatively scarce to a country where they are relatively abundant. The magnitude of the gap allows us to discipline the importance of imperfect substitution.[10]

An important concern is that human capital may not transfer fully across countries due to technology differences, discrimination, licensure, and other barriers.

[10]We abstract from variation of wage gains within skill groups. If workers within skill groups are imperfectly substitutable, the average wage gain of each group could be affected by the composition of its workers. The labor aggregator that we adopt from the literature is not well suited to develop the implications of this kind of heterogeneity.

In Hendricks and Schoellman (2018) we consider a number of ways to gauge the quantitative importance of these concerns. For example, we show that the wage gains of migrants who enter on employment visas, who work the exact same 3-digit occupation before and after migrating, or who move from English-speaking countries are 10-20 percent larger than the average. Alternatively, we show that the average migrant's post-migration job is 16 percent lower paying than their pre-migration job, based on the mean wage of U.S. natives in each. Below, we assess the robustness of our findings to adjusting up wage gains of all migrants or only skilled migrants by 20 percent.

1. Labor Quality Gaps. — Table 3 shows the labor quality gaps implied by equation (14). The table also shows the two ratios that determine these values: observable wage gaps $\Delta \ln (w_j)$ and migrant wage gains π_j. We highlight a number of findings:

1) For all skill cutoffs, the fact that cross-country wage gaps exceed migrant wage gains implies that workers of all skills have higher labor quality in rich compared with poor countries.

2) Higher skill cutoffs are associated with larger wage gaps $\Delta \ln (w_j)$, smaller migrant wage gains, and therefore larger labor quality gaps $\Delta \ln (h_j)$.

3) In the rich country, skilled workers have relatively higher labor quality than in the poor country: $\frac{h_{s,r}/h_{u,r}}{h_{s,p}/h_{u,p}} > 1$. Since migrant wage gains are similar for skilled and unskilled workers, $\frac{h_{s,r}/h_{u,r}}{h_{s,p}/h_{u,p}}$ differs at most 1.6 fold across countries.[11] This limits the size of the imperfect substitutes term in equation (11) (recall that this term vanishes when $h_{s,r}/h_{u,r} = h_{s,p}/h_{u,p} = 1$).

[11] Specifically, with equal skill premiums in rich and poor countries, we have $\frac{h_{s,r}/h_{u,r}}{h_{s,p}/h_{u,p}} = \pi_1/\pi_2 \in [1.4, 1.6]$. This follows from $w_{s,p}/w_{u,p} = p_{s,p}/p_{u,p} \times h_{s,p}/h_{u,p} = w_{s,r}/w_{u,r} = p_{s,r}/p_{u,r} \times h_{s,r}/h_{u,r}$.

Table 3—: Cross-country Labor Quality Gaps

	Skill Cutoff		
	SHS	HSG	SC
$h_{u,r}/h_{u,p}$	2.00	2.00	2.45
$w_{u,r}/w_{u,p}$	7.41	6.90	7.29
π_u	3.71	3.46	2.98
$h_{s,r}/h_{s,p}$	3.24	3.12	3.51
$w_{s,r}/w_{s,p}$	7.41	6.90	7.29
π_s	2.29	2.21	2.08
$\frac{h_{s,r}/h_{u,r}}{h_{s,p}/h_{u,p}}$	1.62	1.57	1.43

Note: The table shows the rich-to-poor country labor quality ratios, $h_{j,r}/h_{j,p}$, and their components according to equation (14). $w_{j,r}/w_{j,p}$ denotes the gap in observable wages of skill group j. π_j is the wage gain at migration.

2. Elasticity Implications. — Using these data moments, we can calculate the long-run elasticity of substitution Ψ from equation (12). Intuitively, the elasticity is low if large variation in the abundance of skilled labor $L_{s,c}/L_{u,c}$ leads to small variation in wage bill ratios $W_{s,c}/W_{u,c}$.

Intuition may be gained from the case where skills are perfect substitutes. With $\Psi = 1$, doubling skilled labor inputs $L_{s,c}/L_{u,c}$ also doubles the wage bill ratio $W_{s,c}/W_{u,c}$. However, if skills are imperfect substitutes, the skill premium declines, dampening the change of the wage bill ratio. The lower the elasticity of substitution, the larger this dampening effect becomes. If the long-run elasticity is one ($\Psi = 0$), the decline in the skill premium fully offsets the rise in $L_{s,c}/L_{u,c}$ and the wage bill ratio no longer changes.

If returns to schooling do not vary across countries, we may rewrite equation (12) in terms of directly observable data moments. For notational convenience, let $\lambda(x)$ for any variable x be defined as $\lambda(x) \equiv \ln\left(\frac{x_{s,r}/x_{u,r}}{x_{s,p}/x_{u,p}}\right) = \Delta \ln(x_s) - \Delta \ln(x_u)$. For example, $\lambda(N)$ denotes the cross-country gap in the relative abundance of skilled labor. Then equation (12) together with $\lambda(W) = \lambda(N) = \lambda(L) - \lambda(h)$

implies

$$\lambda(h) = \frac{1-\Psi}{\Psi}\lambda(N) \tag{15}$$

so that the elasticity of substitution between skilled and unskilled labor is given by

$$\frac{1}{1-\Psi} = 1 + \frac{\lambda(N)}{\lambda(h)}. \tag{16}$$

The latter term may be estimated using $\lambda(h) = \ln(\pi_u/\pi_s)$.

Table 4 shows the corresponding data values for each skill cutoff. We highlight three observations:

1) $\lambda(N) = \ln\left(\frac{N_{s,r}/N_{u,r}}{N_{s,p}/N_{u,p}}\right)$ is positive for all skill cutoffs, indicating that rich countries are abundant in skilled labor.

2) Cross-country variation in relative skilled labor qualities $\lambda(N)$ is much larger than cross-country variation in relative skilled labor qualities $\lambda(h)$. As a result, the elasticity of substitution is always high (at least 4.5).

3) As the skill cutoff is increased, $\lambda(N)$ declines (as previously noted) while $\lambda(h)$ is fairly stable, causing the elasticity to decline as well.

Intuitively, cross-country variation in relative skill prices is limited because migrant wage gains do not vary greatly across skill groups. Reconciling small variation in relative skill prices with large variation in relative labor inputs requires a high elasticity of substitution. Conversely, a smaller long-run elasticity of substitution would imply much larger differences in migrant wage gains between skilled and unskilled workers than we see in the data.[12]

[12]Specifically, for a long-run elasticity of 2, we find $\frac{h_{s,r}/h_{u,r}}{h_{s,p}/h_{u,p}}$ from equation (15), setting $\Psi = 0.5$.

Table 4—: Long-run Elasticity of Substitution

	Skill Cutoff		
	SHS	HSG	SC
Elasticity	7.83	4.53	5.15
$\lambda(N)$	3.31	1.58	1.49
$\lambda(h)$	0.48	0.45	0.36

Note: The table shows the determinants of the long-run elasticity of substitution given by equation (16). $\lambda(N) \equiv \Delta \ln(N_s) - \Delta \ln(N_u)$ denotes the relative abundance of skilled labor in the rich versus poor country. $\lambda(h)$ is the corresponding term for skilled labor quality.

There are several ways of reconciling a high long-run elasticity with smaller empirical estimates. One possibility is that empirical estimates, which are often based on within-country time-series evidence (e.g., Katz and Murphy, 1992), do not capture the full response of technology to large and persistent cross-country variation in labor supplies. Alternatively, the skill bias of technology may in part be determined by factors that do not respond to variation in labor supplies. In that case, cross-country skill bias differences should be treated as partially exogenous in our analysis. We consider this possibility in Section III. Finally, we show in Section IV that a model with capital-skill complementarity implies a long-run elasticity of substitution that is consistent with conventional empirical estimates.

B. Development Accounting Results

We perform development accounting by applying the data moments shown in Section II.A to the closed form solution for $share_L$, equation (11). As shown in Table 5, $share_L$ is close to 60 percent for all skill cutoffs. These findings align closely with Hendricks and Schoellman (2018). Having a closed form solution for $share_L$ allows us to provide sharp intuition for our results.

Using $\pi_u/\pi_s = \frac{h_{s,r}/h_{u,r}}{h_{s,p}/h_{u,p}}$, we find that unskilled wage gains exceed skilled wage gains by factor 4.5 for the SC skill cutoff and by factor 27.5 for the SHS skill cutoff. In the data, the ratio is at most 1.6 (see Table 3).

Table 5—: Closed Form Solution for share$_L$

	Skill Cutoff		
	SHS	HSG	SC
$share_L$	0.63	0.59	0.60
Perfect substitutes term	0.45	0.48	0.54
Imperfect substitutes term	0.19	0.12	0.06
$1/\Psi - 1$	0.15	0.28	0.24
$\ln\left(\frac{W_r/W_{u,r}}{W_r/W_{u,p}}\right)$	1.27	0.42	0.26
$share_K$	0.04	0.04	0.04
$share_z$	0.33	0.37	0.36

Note: The table shows the closed form solution for the human capital share in cross-country output gaps and its components according to equation (11).

Table 5 reveals why $share_L$ is approximately constant across skill cutoffs: variation of the perfect substitutes term and of the imperfect substitutes term roughly balance each other. The perfect substitutes term ranges from 0.45 to 0.56 across skill cutoffs. Recall that the this term is equivalent to the contribution of human capital in a single skill model. It depends on the magnitude of unskilled migrant wage gains relative to the output gap. Since unskilled migrant wage gains are small (3 to 3.7) relative to the output gap (10.7), the contribution of human capital is large. Higher skill cutoffs are associated with smaller unskilled migrant wage gains and therefore larger perfect substitutes terms.

The imperfect substitutes term depends on the elasticity of substitution and the skilled-to-unskilled earnings ratios. The fact that the reduced form elasticity of substitution is high (for reasons that are discussed in Section A.2) limits the size of this term. Since differences in relative labor quantities $N_{s,c}/N_{u,c}$ and therefore also in unskilled labor income shares are much smaller for higher skill cutoffs, the imperfect substitutes term is smaller for higher skill cutoffs. It is the offsetting variation in the perfect substitutes and the imperfect substitutes term that generates the approximate constancy of share_L across skill cutoffs.

For completeness, Table 5 also shows the fraction of output gaps due to physical capital and TFP. As commonly found in the literature, the contribution of physical capital is small (0.04), leaving more than one third of the output gap unexplained and hence attributed to TFP.

C. *Relative Skilled Labor Productivities*

One contribution of our work is to allow for both relative labor quality $\frac{h_{s,r}/h_{u,r}}{h_{s,p}/h_{u,p}}$ and relative skill bias $\frac{\theta_{s,r}/\theta_{u,r}}{\theta_{s,p}/\theta_{u,p}}$ in the same framework and to disentangle the two. Thus, we can contribute to the ongoing debate on which of these two forces accounts for the constancy of skill premiums across countries given the enormous differences in skilled labor supplies.

We estimate relative skill bias gaps based on the firm's first-order condition for labor, which implies

$$\left(\frac{\theta_{s,c}h_{s,c}N_{s,c}}{\theta_{u,c}h_{u,c}N_{u,c}}\right)^{\rho} = \frac{W_{s,c}}{W_{u,c}}. \tag{17}$$

Assuming that returns to schooling do not differ across countries, we have $\lambda(N) = \lambda(W)$ and therefore

$$\lambda(\theta h) = \frac{1-\rho}{\rho}\lambda(N) \tag{18}$$

Recall that, for any variable x, we define $\lambda(x) \equiv \ln\left(\frac{x_{s,r}/x_{u,r}}{x_{s,p}/x_{u,p}}\right)$. Hence, (18) relates differences in the relative abundance of skilled labor $\lambda(N)$ to differences in its relative productivity $\lambda(\theta h)$. The same expression also applies in the case where labor-augmenting technologies are fixed exogenously.

Intuitively, skilled wage premiums appear similar across countries. Given large differences in relative labor supplies $\lambda(N)$ and conventional estimates of the (short-run) elasticity of substitution, some combination of skill bias of technologies ($\lambda(\theta) > 0$) or a relative labor quality per worker advantage ($\lambda(h) > 0$) is required.

Previous work explored versions of equation (18) with one of these two possibilities ruled out, eliminating the identification challenge (Caselli and Coleman, 2006; Jones, 2014). Substantial disagreement has ensued (Caselli and Ciccone, 2019; Jones, 2019).

Our approach is to use the new evidence from the wage gains of migrants to discipline $\lambda(h)$. Implicitly, the remainder is attributed to $\lambda(\theta)$. One way to think about the model with endogenous technology choice is that we calibrate the value of Ψ (and implicitly the curvature of the technology frontier ω) to induce firms to choose $\lambda(\theta)$ as an optimal response to $\lambda(h)$ and $\lambda(N)$. However, we can also measure $\lambda(\theta)$ directly without this structure.

Table 6 shows our results. For typical estimates of the (short-run) elasticity of substitution, the relative skill bias $\frac{\theta_{s,r}/\theta_{u,r}}{\theta_{s,p}/\theta_{u,p}}$ exceeds three. It is larger for low skill cutoffs (because they imply larger $\frac{N_{s,r}/N_{u,r}}{N_{s,p}/N_{u,p}}$, which increases the right-hand side of equation (18)) and smaller values of ρ (which also increases the right-hand side of equation (18)).

Table 7 shows the fraction of cross-country variation in the relative productivity of skilled labor $\lambda(\theta h)$ that is due to labor quality, defined as $\lambda(h)/\lambda(\theta h)$. Since relative skilled labor quality $\lambda(h)$ does not vary with the short-run elasticity of substitution, this fraction varies inversely with the relative skill bias ratios shown in Table 6. For conventional values of the elasticity of substitution (between 1.5 and 2), at most one-third of the cross-country variation in relative skilled labor productivity is due to labor quality. However, the fraction rises rapidly as the elasticity increases.

These findings agree with the previous work of Okoye (2016) and Rossi (2019), who also decompose cross-country variation in the relative productivity of skilled

Table 6—: Relative Skill Bias, Rich vs. Poor Country

Short-run	Skill Cutoff		
Elasticity	SHS	HSG	SC
1.25	3.50×10^5	355.98	274.06
1.50	463.99	15.08	13.83
2.00	16.91	3.10	3.11
3.00	3.23	1.41	1.47
4.00	1.86	1.08	1.15
5.00	1.41	0.95	1.01

Note: The table shows cross-country gaps in the relative skill bias of technology, $\frac{\theta_{s,r}/\theta_{u,r}}{\theta_{s,p}/\theta_{u,p}}$.

labor into the contributions of relative labor quality and technological skill bias. Both use the returns to schooling of foreign-educated immigrants as the extra moment to provide identification (rather than wage gains of immigrants) and conclude that most of the variation can be attributed to technology. If we focus on Rossi's definition of skill (some college or more) and elasticity of substitution (1.5), we find a share of 88 percent, which is very similar to Rossi's share of 90 percent.

D. *Robustness*

The previous discussion reveals that migrant wage gains play a central role for our results. The discussion in Hendricks and Schoellman (2018) addresses a number of concerns related to the interpretation of migrant wage gains as measures of cross-country skill price differences. Here, we address two of these concerns.

The first concern relates to the measurement of unskilled wage gains. The New Immigrant Survey and Latin Migration Project data used by Hendricks and Schoellman (2018) contain few migrants with no secondary education. As a result, the migrant wage gains of this group may be understated. We explore the

Table 7—: Fraction of Relative Skilled Labor Productivity Differences Due to Labor Quality

Short-run	Skill Cutoff		
Elasticity	SHS	HSG	SC
1.25	3.7	7.1	6.0
1.50	7.3	14.2	12.0
2.00	14.6	28.3	24.1
3.00	29.3	56.7	48.2
4.00	43.9	85.0	72.3
5.00	58.5	113.4	96.4

Note: The table shows $100 \times \lambda(h) / \lambda(\theta h)$ where $\lambda(h) \equiv \ln\left(\frac{h_{s,r}/h_{u,r}}{h_{s,p}/h_{u,p}}\right)$ denotes relative skilled labor quality endowments and $\lambda(h\theta)$ denotes relative skilled labor productivity differences between rich and poor countries.

robustness of our findings by increasing the wage gains of this education group to the point where their human capital no longer differs across countries.

The closed form solution for $share_L$ given by equation (11) reveals that increasing the unskilled wage gain π_u has two opposing effects on $share_L$. First, the perfect substitutes term declines because higher wage gains indicate larger contributions of "country" to output gaps. Second, the imperfect substitutes term increases because the elasticity of substitution is reduced according to (12). Intuitively, larger unskilled migrant wage gains imply that $\Delta \ln(h_u)$ declines while $\Delta \ln(h_s)$ is held fixed. As a result, the relative abundance of skilled labor increases in the rich country. Matching the observed wage bill ratios then requires a smaller elasticity of substitution.

Quantitatively, the net result is that $share_L$ declines modestly, as shown in Table 8. Depending on the skill cutoff, it ranges from 0.54 to 0.6. The substitution elasticities decrease to values between 3 and 4. Our findings are now close to the preferred parameterizations of Jones (2014) who assumes $\Delta \ln(h_u) \approx 0$ and sets the elasticity of substitution based on published empirical estimates. Accurately estimating unskilled wage gains is challenging. It is therefore reassuring that our development accounting results are highly robust in this dimension.

The second concern mainly affects the measurement of skilled wage gains. If skills transfer only imperfectly across countries, the assumption that migrant wage gains equal skill price gaps ($\pi_j = p_{j,r}/p_{j,p}$) is violated. Hendricks and Schoellman (2018) consider a variety of data adjustments to address this problem and conclude that imperfect skill transferability reduces skilled migrant wages by 10-20 percent. The third panel of Table 8 shows that accounting for this reduces the role of human capital in accounting for cross-country income differences modestly. We have performed similar robustness checks for all of the model versions that we consider with very similar results. Details are available upon request.

These first two robustness checks show that allowing for smaller wage gains (or smaller cross-country differences in skill price gaps) for only unskilled or skilled migrants does not change our conclusions much. However, our findings would change if we estimated smaller wage gains (or otherwise inferred smaller cross-country differences in skill price gaps) for both groups. For example, if skill transferability affects both groups of workers, then we would estimate that skill price gaps for both types are 20 percent larger than in our baseline. With constant returns to scale in the aggregate production function, it follows directly that $share_L$ declines by 8 percent $(\ln(1.2)/\Delta\ln(Y) = 0.08)$.

Consistent with the evidence collected by Caselli (2016) and Jedwab et al. (2020), the baseline calibration assumes that Mincer returns are the same for rich and poor countries. However, some studies find that Mincer returns decline with the level of development (Caselli, 2005; Psacharopoulos and Patrinos, 2018). The fourth panel of table Table 8 investigates this possibility by setting the rich (poor) country Mincer return to 0.08 (0.12). We find that the resulting human capital share is very close to the baseline case. In the closed from solution for $share_L$, the perfect substitutes term does not depend on Mincer returns and therefore remains unchanged. The imperfect substitutes term is affected by two opposing changes. The gap in the skilled-to-unskilled wage bill ratio $\ln\left(\frac{W_{s,r}/W_{u,r}}{W_{s,p}/W_{u,p}}\right)$ declines because the relative earnings of skilled workers rise in poor countries, where Mincer returns are now higher, but fall in rich countries where they are lower. This reduces the imperfect substitutes term. At the same time, the long-run elasticity of substitution declines which increases the imperfect substitutes term. The overall effect on $share_L$ is small.

Throughout, we assume that the labor income share does not differ across countries. This assumption follows the literature and is consistent with the empirical evidence of Gollin (2002) and Bernanke and Gürkaynak (2001). However, Monge-Naranjo, Sánchez and Santaeulàlia-Llopis (2019) point out that the share of income received by natural resources varies inversely with per capita GDP. This finding suggests that the share of produced output earned by labor is about ten percent higher in poor versus rich countries. We show in Appendix B that $share_L$ increases by $\Delta \ln(1-\alpha)/\Delta \ln(Y)$ when we allow labor shares to differ across countries. A ten percent gap in labor shares therefore increases $share_L$ by about $\ln(1.1)/\ln(10.7) = 0.04$. The same quantitative adjustment can be applied to any of the models that we consider. We do not apply it as the baseline to ensure that our results are consistent with the literature that we address.

III. Exogenous Technology Model

We now consider a model where the skill bias of technology does not respond to the abundance of skilled labor. The *exogenous technology model* shares the production function (1) and the labor aggregator (2) with the endogenous technology model, but it drops the technology frontier. While the endogenous technology model assumes that all cross-country variation in technological skill bias is attributable to labor endowments, the exogenous technology model assumes that all of the variation is exogenous.[13] The development accounting implications of the two models therefore bound the implications of a more general setup where technological skill bias is partially an endogenous response to labor endowments and partially a response to other, exogenous factors.

A. Development Accounting Approach

Development accounting assesses how each factor input affects steady state output. As pointed out by Caselli and Ciccone (2019), the effect of changing labor inputs is not uniquely determined when skilled labor and technological skill bias are complements; it depends on the reference country's technology. The endogenous technology model sidesteps this issue because the skill bias of technology is varies with labor endowments. Now that the skill bias of technology is taken as fixed, we confront this issue by considering two definitions of $share_L$:

1) $share_L^{poor}$ fixes the skill bias of technology at the poor country level. Intuitively, this corresponds to the effect of increasing the poor country's labor inputs to the rich country's levels.

2) $share_L^{rich}$ fixes the skill bias of technology at the rich country level. Intuitively, this corresponds to the effect of reducing the rich country's labor inputs to the poor country's levels.

B. Closed Form Solution

We derive a closed form solution for $share_L^{poor}$ and $share_L^{rich}$ in terms of observable data moments.

[13] We continue to refer to $\theta_{j,c}$ as technological skill bias, recognizing that its variation may be due to factors other than technology, as argued by Caselli and Ciccone (2019).

PROPOSITION 3: *The share of labor inputs evaluated at poor country skill bias is given by*

$$(19)\quad share_L^{poor} = \underbrace{1 - \frac{\ln\left(\frac{p_{u,r}}{p_{u,p}}\right)}{\Delta\ln(Y)}}_{\text{perfect substitutes}} + \underbrace{\frac{\frac{1}{\rho}\ln\left(\frac{1+\frac{W_{s,p}}{W_{u,p}}\left(\frac{L_{s,r}/L_{u,r}}{L_{s,p}/L_{u,p}}\right)^{\rho}}{1+W_{s,p}/W_{u,p}}\right) - \ln\left(\frac{W_r/W_{u,r}}{W_p/W_{u,p}}\right)}{\Delta\ln(Y)}}_{\text{imperfect substitutes}}.$$

When evaluated at rich country skill bias, the share of labor inputs is given by

$$(20)\quad share_L^{rich} = \underbrace{1 - \frac{\ln\left(\frac{p_{u,r}}{p_{u,p}}\right)}{\Delta\ln(Y)}}_{\text{perfect substitutes}} + \underbrace{\frac{\frac{1}{\rho}\ln\left(\frac{1+W_{s,r}/W_{u,r}}{1+\frac{W_{s,r}}{W_{u,r}}\left(\frac{L_{s,r}/L_{u,r}}{L_{s,p}/L_{u,p}}\right)^{-\rho}}\right) - \ln\left(\frac{W_r/W_{u,r}}{W_p/W_{u,p}}\right)}{\Delta\ln(Y)}}_{\text{imperfect substitutes}}$$

PROOF:

Section C.C1.

Both expressions resemble the closed form solution for $share_L$ obtained from the endogenous technology model, equation (11).[14] In both cases, the perfect substitutes term is the same and represents the contribution of labor inputs with a single skill.

The imperfect substitutes term depends on the elasticity of substitution between skilled and unskilled labor (now governed by the short-run elasticity parameter ρ) and on the labor income ratios $W_{s,c}/W_{u,c}$. The imperfect substitutes term is small when skilled labor is "unimportant" in the sense of earning little income, so that $W_{s,c}/W_{u,c}$ is small, or when relative labor supplies $\frac{L_{s,r}/L_{u,r}}{L_{s,p}/L_{u,p}}$ are similar across countries.

[14]In fact, when $\rho = \Psi$, given by equation (12), $share_L^{poor} = share_L = share_L^{rich}$ because $W_{s,p}/W_{u,p}\left(\frac{L_{s,r}/L_{u,r}}{L_{s,p}/L_{u,p}}\right)^{\Psi} = W_{s,r}/W_{u,r}$.

C. Quantitative Results

We calibrate the model to match the same data moments that were used in the calibration of the endogenous technology model. However, $share_L$ now depends on the short-run elasticity of substitution. The data moments are therefore not sufficient to perform development accounting. Following Jones (2014), we explore a range of values for ρ.

Table 9 shows the share of output gaps accounted for by labor inputs, evaluated at poor country skill bias values. For conventional values of the elasticity of substitution between 1.5 and 2 (Ciccone and Peri, 2005), $share_L^{poor}$ ranges from 50 percent to 56 percent. For lower elasticities, especially for the SHS skill cutoff, $share_L^{poor}$ can drop below 50 percent. However, it is worth keeping in mind that these cases imply extremely large cross-country differences in skill bias (see Table 6).[15] As the elasticity approaches the value implied by the model with the technology frontier (Ψ), $share_L^{poor} \to share_L$.

Table 10 shows the corresponding results when the contribution of labor inputs is evaluated using rich country skill bias parameters. For substitution elasticities in the conventional range between 1.5 and 2, $share_L^{rich}$ ranges from 65 percent to 74 percent. Across all cells, the range is only modestly wider.

To understand the diverging patterns between $share_L^{rich}$ and $share_L^{poor}$, it is useful to remember from Table 2 that the relative abundance of skilled labor $\frac{N_{s,r}/N_{u,r}}{N_{s,p}/N_{u,p}}$ is much larger with lower skill cutoffs such as SHS. In order to fit the targets, our calibration infers much larger gaps between rich and poor countries in labor augmenting technologies $\frac{\theta_{s,r}/\theta_{u,r}}{\theta_{s,p}/\theta_{u,p}}$ in this case. Thus, development accounting results become much more sensitive to whether we use poor or rich country technologies as the benchmark. Equations (19) and (20) show that this effect interacts with ρ,

[15] For any given value of ρ, the model implies the same values for labor quality $h_{j,c}$ and relative skill bias gaps $\frac{\theta_{s,r}/\theta_{u,r}}{\theta_{s,p}/\theta_{u,p}}$ as the model with the technology frontier. Since changing all $\theta_{j,c}$ by a common factor is equivalent to varying total factor productivity z_c, the skill bias parameters are only identified up to country specific constants.

so that the divergence is larger as the elasticity of substitution moves away from the value we calibrated in the endogenous skill bias case.

Compared with the endogenous technology model, the contribution of labor inputs to cross-country output gaps remains similar, though the range of uncertainty is now wider. Even without resolving the difficult question to what extent the skill bias of technology responds endogenously to labor supplies, we conclude that labor supplies account for between one-half and three-fourths of cross-country output gaps.

D. *Comparison to Literature*

Now that we have considered both our new model with endogenous skill bias of technology and a more standard framework with exogenous skill bias, this section discusses why our development accounting results differ from the findings of the recent literature. While we conclude that labor inputs account for between one-half and three-fourths of output gaps, the literature contains a much wider range (Caselli and Ciccone, 2013; Jones, 2014; Caselli and Ciccone, 2019; Jones, 2019).

The disagreement revolves around two questions. First, how large is the elasticity of substitution between skilled and unskilled labor? Jones (2014) argues that development accounting is very sensitive to its value. Second, are relative skilled labor productivities embodied in workers as human capital or in technology? Lacking direct evidence, the previous literature assumes that cross-country differences in unskilled labor qualities are small (or zero). In terms of our decomposition of $share_L$ (equation (11)), the literature disagrees about the magnitude of the imperfect substitutes term while assuming that the perfect substitutes term is (close to) zero.

Our main departure from the literature is to use evidence related to migrant wage gains to discipline cross-country differences in labor qualities, $h_{j,r}/h_{j,p}$. This, in effect, reverses the conclusions of the literature. We find that the perfect substitutes term is large. Uncertainty about the magnitude of the imperfect substitutes term is then no longer of first-order importance.

The first key data moment is the wage gain of unskilled migrants. Since this wage gain is about half as large as output gaps, $\pi_u \approx 0.5\Delta \ln(Y)$, we infer that the perfect substitutes term is at least 0.45. Since the imperfect substitutes term is positive, human capital must account for at least 45 percent of output gaps, even before imperfect substitution is taken into account. This rules out small values for $share_L$.

The second key data moment is the wage gain of skilled workers. From the fact that this is broadly similar to the unskilled wage gain we infer that relative labor qualities $h_{s,c}/h_{u,c}$ do not differ greatly across countries. It follows that the role of imperfect substitution is limited. The value of the short-run elasticity of substitution between skilled and unskilled labor is then no longer of first-order importance.

Similarly, whether technological skill bias responds to labor endowments or is determined by exogenous factors that we do not model is also no longer of first-order importance. If technological skill bias is exogenous, the majority of cross-country variation in relative skilled labor productivities are not due to human capital. If skill bias is endogenous, the long-run elasticity of substitution must be high. In both cases, the role of imperfect substitution for output gaps (the imperfect substitutes term) is limited.

Clearly, our analysis relies heavily on empirical evidence about migrant wage gains. It leads us to conclude, in contrast to the literature, that unskilled workers are endowed with substantially higher labor quality in rich versus poor countries. However, the robustness analysis shows that reasonable adjustments to the wage gains of different groups of workers do not materially alter our conclusions. Our development accounting results remain largely unchanged, even if we follow Jones (2014) in assuming that unskilled labor quality does not differ across countries

$(h_{u,p} = h_{u,r})$. The perfect substitutes term in equation (11) is then smaller, but relative labor quality gaps $\frac{h_{s,r}/h_{u,r}}{h_{s,p}/h_{u,p}}$ and therefore also the imperfect substitutes term are larger. It follows that the key data moment is the skilled migrant wage gain, which is more precisely estimated than the unskilled wage gain.

IV. Capital-skill Complementarity

In this section, we consider capital-skill complementarity as an additional source of cross-country variation in skilled labor productivity. In the main text, we only consider the endogenous technology version of the model, leaving the details of the exogenous technology version for Section E.E4.

A. Model Specification

The specification of the aggregate production function is based on Krusell et al. (2000). Output per worker Y_c is produced according to

$$Y_c = S_c^{\alpha} \left(z_c L_c\right)^{1-\alpha} \tag{21}$$

where

$$L_c = \left[(\theta_{u,c} L_{u,c})^{\rho} + (\theta_{s,c} Z_c)^{\rho}\right]^{1/\rho} \tag{22}$$

and

$$Z_c = \left[(\mu_e E_c)^{\phi} + (\mu_s L_{s,c})^{\phi}\right]^{1/\phi} \tag{23}$$

with parameters $\alpha, \rho \in (0,1)$, $\phi < 1$, and $\mu_e, \mu_s > 0$.

S_c denotes structures per capita. L_c is given by a CES aggregator of unskilled labor $L_{u,c}$ and a composite input Z_c, which is in turn a CES aggregator of skilled labor $L_{s,c}$ and equipment per worker E_c. The skill bias parameters $\theta_{j,c}$ are constrained by the technology frontier (3) with $B_c = 1$ taken as fixed. The endogenous technology model emerges as a special case when $\mu_e = 0$ so that $Z_c = L_{s,c}$.

As before, we assume that the economy is in steady state with an interest rate that is equal to the discount rate of the infinitely lived representative agent. This fixes the rental prices of equipment $q_{e,c}$ and structures $q_{s,c}$ and therefore also S_c/Y_c. The representative firm solves

$$\max_{S_c, E_c, L_{j,c}, \theta_{j,c}} Y_c - q_{s,c} S_c - q_{e,c} E_c - \sum_j p_{j,c} L_{j,c} \tag{24}$$

subject to (21), (22), (23), and the frontier constraint (3).

B. *Reduced Form Labor Aggregator*

Similar to the endogenous technology model, we are able to derive a reduced form labor aggregator that substitutes out the firm's optimal skill bias choices.

PROPOSITION 4: *Substituting out the firm's optimal skill bias choices yields the reduced form labor aggregator*

$$L_c = B_c \left([L_{u,c}/\kappa_u]^{\Psi} + [Z_c/\kappa_s]^{\Psi} \right)^{1/\Psi} \tag{25}$$

with $\Psi = \frac{\omega\rho}{\omega - \rho}$ *as in the endogenous technology model.*

PROOF:

Section E.E3

C. Development Accounting

Development accounting proceeds analogously to the endogenous technology model. Starting from

$$Y_c = (S_c/Y_c)^{\alpha/(1-\alpha)}\, z_c L_c \tag{26}$$

the output gap can be additively separated into the contributions of TFP, structures, and labor inputs jointly with equipment:

$$\underbrace{\Delta \ln (Y)}_{\text{output gap}} = \underbrace{\Delta \ln (z)}_{\text{TFP}} + \underbrace{\Delta \ln \left((S/Y)^{\alpha/(1-\alpha)} \right)}_{\text{structures}} + \underbrace{\Delta \ln (L)}_{\text{labor and equipment}} \tag{27}$$

The share of the output gap accounted for by each input is given by

$$1 = \underbrace{\frac{\Delta \ln (z)}{\Delta \ln (Y)}}_{\text{share}_z} + \underbrace{\frac{\Delta \ln \left((S/Y)^{\alpha/(1-\alpha)} \right)}{\Delta \ln (Y)}}_{\text{share}_S} + \underbrace{\frac{\Delta \ln (L)}{\Delta \ln (Y)}}_{share_{L+E}} \tag{28}$$

The joint contribution of labor inputs and equipment has a closed form solution in terms of data moments (see Section E.E3). It may be subdivided into the separate contributions of its components ($h_{j,c}$, $N_{j,c}$, E_c). These are defined as the changes in steady state output that result from changing each input from its poor country value to its rich country value, holding the rental prices of equipment and structures fixed. The counterfactual output changes depend on the fixed equipment rental prices. We therefore define two versions of each input's share. Superscript "poor" fixes q_E at the poor country's level. Superscript "rich" fixes them at the rich country's level.

As in the endogenous technology model, the development accounting implications depend on the reduced form curvature parameter Ψ, but not on the separate values of ρ and ω.

D. Calibration

We calibrate the model using the same data moments that were used for the endogenous technology model. However, we replace the moments related to capital inputs with separate moments for equipment and structures.

Specifically, we construct equipment/output ratios (E_c/Y_c) and structures/output ratios (S_c/Y_c) from Penn World Table 9 (Feenstra, Inklaar and Timmer, 2015) and International Comparison Program data (World Bank, 2014). The income share of equipment $IS_{e,r} = 0.15$ is taken from Valentinyi and Herrendorf (2008). Together with a capital share of 0.33, this implies an income share for structures of $IS_{s,r} = 0.18$, which is consistent with Valentinyi and Herrendorf (2008). We lack data on equipment and structures shares for low income countries. Since we find that S_c/Y_c and the relative price of structures versus consumption are similar for rich and poor countries, we set $IS_{s,c} = 0.18$ for all countries. These data moments are summarized in Table 11.

In total, we have 14 data moments (6 independent factor incomes shares, 2 output levels, 2 wage gains at migration, 4 capital/output ratios). However, choosing units of E to normalize $\kappa_u = 1$ means that we need to replace the data moments E_c/Y_c with E_r/E_p.[16] This leaves us with 13 data moments that can be used to calibrate the model's 13 parameters (z_c; α; $h_{j,c}$, where $h_{u,r} = 1$; E_c and S_c; Ψ, ϕ).

E. Development Accounting Results

Table 12 summarizes the development accounting implications. Across skill cutoffs, labor inputs and equipment jointly account for around three-quarters of

[16] We also normalize $h_{u,r} = 1$ so that $L_{u,r} = N_{u,r}$. We set $\mu_s = 1$ by choosing units of h_s. We may normalize μ_e, κ_s and B_c to 1 as varying them has the same effect as varying z_c.

cross-country output gaps. Using poor country equipment prices, human capital accounts for 61 percent to 65 percent of output gaps. Using the lower rich country equipment prices, the share is moderately higher, ranging from 67 percent to 70 percent. Since skilled labor and equipment are complements, increasing labor inputs has larger effects on output when equipment is abundant.

The reduced form elasticities of substitution $1/(1-\Psi)$ are much smaller than in the model without capital-skill complementarity. The intuition is based on the observation that Z/L_u varies more across countries than L_s/L_u. At the same time, the relative income share of Z versus L_u varies less than that of skilled versus unskilled labor. Hence, a smaller elasticity reconciles cross-country variation in factor endowments and factor income shares. For the higher skill cutoffs, the elasticities of substitution are in line with conventional estimates for the short-run elasticity.

For completeness, Table 13 summarizes the shares of output gaps accounted for by other inputs evaluated at poor country equipment prices. Structures make essentially no contribution. Equipment contributes about 6 percent. The contribution of TFP is given by $1 - share_S - share_{L+E}$ and therefore amounts to about 24 percent.[17] The complementarity of skilled labor and equipment implies that jointly increasing both inputs has a larger effect on output than increasing each input separately. This explains why $share_{L+E}$ is almost ten percentage points larger than $share_L + share_E$.

We also explore a version of the model where the skill bias of technology is taken as exogenous. For conventional values of the elasticity of substitution between skilled and unskilled labor, we find that $share_L$ ranges from 52 percent to 74 percent. Details are relegated to Section E.E4.[18]

[17] The results are very similar when we use rich country equipment prices instead. The contribution of equipment is defined as the steady state output change induced by changing q_E from $q_{E,p}$ to $q_{E,r}$ holding q_S fixed (its level does not matter).

[18] These findings are robust to reasonable variations in the equipment stocks or equipment income shares that we use as calibration targets. For example, $share_L$ remains above one-half even if we reduce the poor country's equipment stock to one quarter of its estimated value. $share_L$ remains above 0.46

Finally, Table 14 shows the fraction of the cross-country variation in relative skilled labor productivities that is due to labor quality. This is defined as $\lambda(h)/\lambda(\theta h)$ where $\lambda(h) \equiv \Delta \ln(h_s) - \Delta \ln(h_u)$ denotes the gap in relative labor quality endowments. Even if attention is restricted to conventional values of the elasticity, the fraction due to labor quality ranges from 8 percent to 68 percent.

To understand this result, note that relative human endowments $\lambda(h)$ are the same across all models. Therefore, relative skilled labor quality in the rich country is at most 1.6 times larger than in the poor country. The previous conclusion that labor quality accounts for modest variation in relative skilled labor productivities remains valid. However, the presence of capital-skill complementarity reduces the variation in relative skill bias needed to account for the observable skill premiums in both countries, so that $\lambda(\theta)$ declines relative to the models without capital-skill complementarity. When the short-run elasticity of substitution is large enough, cross-country variation in skill bias vanishes and labor quality accounts for all of the (modest) variation in relative skilled labor productivities.

V. Conclusion

We evaluate the contribution of human capital for development accounting and the relative productivity of skilled versus unskilled labor. We do so in an environment with imperfect substitution between skill types and a variety of factors that shift relative labor supply or demand. Our approach utilizes new empirical evidence on the average wage gains of migrants and the relative wage gains of skilled versus unskilled migrants from Hendricks and Schoellman (2018).

We find that human capital accounts for at least 45 percent of cross-country income differences. The lower bound of this range is disciplined by the fact that the average wage gains for migrants are small relative to income gaps. This figure is further expanded by the fact that poor countries are particularly scarce

when the the poor country's equipment income share is reduced by half.

in skilled labor and their skilled labor is of lower quality. The overall figure is between one-half and three-quarters depending on which version of the model we consider. We also find that the main driver of cross-country variation in relative skilled labor productivity is skill biased technology, in line with Okoye (2016) and Rossi (2019). This result is disciplined by the fact that the wage gains of unskilled migrants are not too much larger than those of skilled migrants, which suggests that migration to a skill-abundant country is largely offset by more skill-biased technologies.

This paper is designed to speak to an existing literature and therefore works within the canonical framework with a CES labor aggregator for unskilled and skilled workers. While we extend this framework in several ways, we also see a number of interesting directions for future research.[19] One direction would be to relax the assumption of a single CES labor aggregator. For example, structural transformation and urbanization imply large differences in the structure of production across countries. It would be interesting to explore whether the skill bias or substitutability of labor varies by sector and whether this affects the conclusions here, as Malmberg (2019) does within manufacturing industries. Alternatively, one could explore frameworks without the CES aggregator entirely. For example, assignment models include a notion of labor supply, labor demand, and wages that vary continuously with skill, rather than discretely at a pre-determined education level separating unskilled from skilled workers. Such models would provide an alternative framework to examine these issues.

[19]We are grateful to several referees for suggesting these extensions for future work.

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Table 8—: Robustness

	Skill Cutoff		
	SHS	HSG	SC
Baseline			
$share_L$	0.63	0.59	0.60
Perfect substitutes term	0.45	0.48	0.54
Imperfect substitutes term	0.19	0.12	0.06
No human capital gaps for least skilled workers			
$share_L$	0.60	0.54	0.57
Perfect substitutes term	0.15	0.34	0.48
Imperfect substitutes term	0.45	0.20	0.09
Skilled wage gain increased by 20 percent			
$share_L$	0.56	0.55	0.57
Perfect substitutes term	0.45	0.48	0.54
Imperfect substitutes term	0.12	0.07	0.03
Higher Mincer returns in low income countries			
$share_L$	0.63	0.60	0.60
Perfect substitutes term	0.45	0.48	0.54
Imperfect substitutes term	0.19	0.12	0.06

Note: The table shows the fraction of cross-country output gaps that is due to human capital, $share_L$, and decomposes it into perfect substitutes and imperfect substitutes terms according to equation (11). The first panel shows the endogenous technology model. The second panel sets the wage gains for migrants with no secondary schooling such that their labor quality does not differ across countries. The third panel increases skilled wage gains by 20 percent relative to the estimates of Hendricks and Schoellman (2018). The fourth panel sets the Mincer return in the rich (poor) country to 0.08 (0.12).

Table 9—: Development Accounting with Poor Country Skill Bias

Short-run Elasticity	Skill Cutoff SHS	HSG	SC
1.25	0.44	0.48	0.50
1.50	0.50	0.51	0.52
2.00	0.56	0.54	0.55
3.00	0.60	0.57	0.58
4.00	0.61	0.59	0.59
5.00	0.62	0.60	0.60
Endogenous θ	0.63	0.59	0.60

Note: The table shows the human capital share in cross-country output gaps $share_L^{poor}$ for selected values of the elasticity of substitution between skilled and unskilled labor (rows) and for selected skill cutoffs (columns). The last row shows the contribution of labor inputs when skill bias is endogenous, $share_L$, taken from Table 5.

Table 10—: Development Accounting with Rich Country Skill Bias

Short-run Elasticity	Skill Cutoff SHS	HSG	SC
1.25	0.75	0.71	0.71
1.50	0.74	0.68	0.68
2.00	0.72	0.65	0.65
3.00	0.69	0.62	0.62
4.00	0.67	0.60	0.61
5.00	0.65	0.59	0.60
Endogenous θ	0.63	0.59	0.60

Note: The table shows the human capital share in cross-country output gaps $share_L^{rich}$ for selected values of the elasticity of substitution between skilled and unskilled labor (rows) and for selected skill cutoffs (columns). The last row shows the contribution of labor inputs when skill bias is endogenous, $share_L$, taken from Table 5.

Table 11—: Additional Calibration Targets

	S/Y	E/Y
Rich	2.81	0.37
Poor	2.85	0.14
Ratio	0.98	2.62

Table 12—: Development Accounting with Capital-skill Complementarity

	Skill Cutoff		
	SHS	HSG	SC
$share_L^{poor}$	0.65	0.61	0.62
$share_L^{rich}$	0.68	0.67	0.70
$share_{L+E}$	0.78	0.75	0.76
Elasticity	4.77	2.51	2.17

Note: The table shows the human capital share in cross-country output gaps for selected skill cutoffs (columns). $share_L^{poor}$ $\left(share_L^{rich}\right)$ uses poor (rich) country equipment prices. $share_{L+E}$ denotes the joint share of human capital and equipment. The last row shows the long-run elasticity of substitution between unskilled labor and the skilled labor/equipment aggregator Z.

Table 13—: Development Accounting with Poor Country Equipment Prices

	Skill Cutoff		
	SHS	HSG	SC
$share_L$	0.65	0.61	0.62
$share_E$	0.07	0.06	0.05
$share_S$	0.00	0.00	0.00
$share_z$	0.22	0.25	0.24

Table 14—: Fraction of Relative Skilled Labor Productivity Variation Due to Labor Quality

Short-run	Skill Cutoff		
Elasticity	SHS	HSG	SC
1.25	3.8	8.7	8.9
1.50	7.9	19.1	21.2
2.00	16.9	48.3	67.8
3.00	38.9	203.7	n/a
4.00	68.7	n/a	n/a
5.00	111.3	n/a	n/a

Note: The table shows $100 \times \lambda(h) / \lambda(\theta h)$ where $\lambda(h) \equiv \Delta \ln(h_s) - \Delta \ln(h_u)$ denotes the cross-country gap in relative skilled labor quality endowments. This is not defined for cases where the rich country's technology is less skill biased than the poor country's technology.