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Skill Bias, Technology Frontiers, Barriers to Adoption, and the Effects of Trade: A Panel Data Analysis

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Economic models are necessarily simplifications. To this end, an important consideration in macroeconomics is how to best model the aggregate economy and the aggregate production function. Having experienced quite a significant rise to prominence in macroeconomic analysis, the starting point of much aggregate research has focused on the Cobb-Douglas model as a representation of the aggregate economy. Accordingly, an extensive avenue of analysis has been attempting to conceptualize and evaluate how this aggregate model varies across country and across time.

While the simplicity of the Cobb-Douglas form is a valuable feature, it has limitations and implications. In canonical Cobb-Douglas specifications, a single multiplicative "total factor productivity" (TFP) is assumed. This implies that all factor-specific technical efficiencies are perfectly correlated. Further, in canonical Cobb-Douglas specifications, often only unitary broad aggregate factor measures are used – that is, *the* labor endowment, *the* capital stock. This implies that sub-groups within the factor aggregate are perfect substitutes in production. Of particular focus here will be the nature of the "skilled" and "unskilled" labor subgroups of the labor aggregate. Moreover, most studies of cross-country income variation employing the single multiplicative TFP framework find that GDP per capita and TFP are robustly positively related. Taken together, this implicitly asserts that richer countries use *all* factors of production more efficiently, and accordingly that poorer countries, using inferior and inappropriate technology, use *all* factors of production less efficiently.

In their seminal paper, *"The World Technology Frontier,"* Caselli and Coleman (2006) study the aggregate production function with non-neutral technology when skilled and unskilled labor are allowed to be imperfect substitutes. They study cross-country technology differences and labor endowments for 52 countries in the year 1988, and uncover skill bias in these cross-country technology differences. They find strong evidence of *negative* relation between these factor efficiencies, and this observed tradeoff between skilled labor efficiency and unskilled labor efficiency leads them to conclude that a proverbial 'world technology frontier' exists. Moreover, they find that these relative factor efficiencies are systematically related to relative labor endowments. They surmise that richer, skilled-labor abundant countries, choose skilled-labor augmenting technology, and that poorer, unskilled-labor abundant countries choose unskilled-labor augmenting technology. In the face of these observations, they propose a simple model to rationalize country-specific technology choices. Given that many of the world's poor countries lie well within the world technology frontier, and given that substantial output gains could be realized if poor countries could access frontier technology, they conclude that barriers to

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technology adoption and absorption contribute substantively to the observed variation in cross-country income.

In this dissertation, I strictly follow and expand upon their framework and methodology, and make three main contributions. First, I extend their approach both across entity and across time by performing a similar analysis for a set of 114 countries from 1950 to 2014. I confirm their main findings of persistent skill bias in cross-country technology efficiencies. Further, given that I construct panel data rather than cross-sectional data, the time series dimension allows me to add a dynamic aspect to the framework, and accordingly I map and analyze the evolution of technology frontiers. I find that the evolution of technology frontiers largely squares with the stylized facts on realized economic growth over the second half of the 20th and early 21st centuries. Moreover, I find that these results are robust to a host of model parameter calibrations. Second, I define a novel "technology space" variable in order to perform some counterfactual and development accounting calculations. In my panel data, I confirm what Caselli and Coleman (2006) find in their cross- sectional analysis – that is, that substantial output gains could be realized if barriers to technology adoption were eliminated, and that these barriers can account for approximately 48% of the observed variation of income differences across countries. Third, I attempt to provide a causal explanation of the evolution of barriers to technology adoption over my sample by investigating the effect of trade on a country's available technology space. I employ an instrumental variable two-stage least squares estimation approach, relying on the geography-based time-variant trade instrument constructed in Magistretti and Tabellini (2019). I find that trade has a robust and statistically significant causal effect on a country's technology space, with my estimates indicating that a 10% increase in trade volume gives rise to approximately a 3% increase in a country's available technology space.

II. Related Literatures

By following closely and building substantively upon Caselli and Coleman (2006),[1] this dissertation is part of, and nests well within, the intersections of the appropriate technology, barriers to adoption, development accounting, and the returns to trade literatures.

Much research and analysis has been devoted to understanding how to model the aggregate economy, and to what fraction of economic growth could be attributed to factors of production and what fraction could be attributed to the residual TFP (see Solow, 1957; Jorgenson and Griliches, 1967). Specifically, building upon the seminal paper by Mankiw et al. (1992), much empirical and theoretical work exploring cross-country growth regressions was produced in response (see Islam, 1995; Hall and Jones, 1999) and a consensus view emerged that factor inputs, while important, could not explain all of observed cross-country income variation. Indeed, the traditional solution to this puzzle has been to assume that a single factor-neutral productivity term is what sets apart the aggregate production functions of poor and rich countries, with poorer countries being less productive/efficient on the whole when compared to

[1] Their working paper Caselli and Coleman (2000) is also highly informative.

richer countries.[2] Yet, this notion of a single multiplicative TFP, among other aspects in the canonical literature, have proven to be overly simplistic assumptions.

In an attempt to better understand the nature of productivity and technical efficiency variations across countries, and the observed cross-country variation in income, several distinct yet complementary literatures have evolved.

Principally, a literature of appropriate technology arose out of the seminal work by Stiglitz and Atkinson (1969), (see Diwan and Rodrik, 1991; Basu and Weil, 1998; Acemoglu and Zilibotti, 2001). Appropriate technology choice is the idea that countries with different factor endowments will employ different technologies. In this literature, there exists a frontier of optimal efficient technologies, rather than a single state-of-the-art technology. Further, a country's technology choice is an endogenous outcome arising from the country's particular factor endowments. Emphasis is there- fore placed on the assertion that countries' particular factor endowments will induce them to make optimally different technology choices given their technology frontiers. This literature is closely related to the literature on innovation and on directed technical change, which investigates whether technical change is biased toward certain factors of production (see Acemoglu, 1998; Jones, 2005). Here, technological change can be biased if productivity improvements and efficiency increases systematically favor a particular abundant factor of production vis-à-vis the other less-abundant factors of production.

Additionally, a literature emerged that places emphasis on the barriers to technology adoption as an important determinant of technological variation and ultimately income variation (see Parente and Prescott, 1994; Eaton and Kortum, 2001). Barriers to technology adoption is broadly the idea that there exists some set of factors which impede the diffusion of technological advancements and hamper the capacity of certain countries to adopt new technologies. A plethora of interpretations and observations have been entertained in this literature - Acemoglu and Robinson (2006) focus on the role of political elites and institutions in impeding technological change; Parente and Prescott (1999) evaluate the effect of monopoly control in markets leading to inefficient technologies and impeding technological adoption; Ferraro (2017) considers the impact of growth volatility as a barrier to technology diffusion. In the pursuit of fully explaining the data on cross-country income variation, there have been some attempts to combine the appropriate technology aspect with the barriers to adoption aspect (along with other considerations) into a single unified growth theory (see Gancia and Zilibotti, 2009; Gancia et al., 2011).

Finally, my dissertation adds to the growing body of work that builds upon or implements in a novel way the framework in Caselli and Coleman (2006), which includes: Alesina et al. (2015) evaluates the impact of labor market regulations on labor productivities; Atesagaoglu et al. (2018) considers the impact of the informal economy on factor productivities; Li (2010) analyzes factor productivities of multinational subsidiaries; Rossi (2017) similarly evaluates the variation of the productivities of skilled and unskilled labor across countries but uses micro-data on skill premia; Growiec (2012) studies the world technology frontier with a non-parametric data

[2] For an overview, see surveys of the field in Caselli (2004) and Hsieh and Klenow (2010).

envelopment analysis approach and still finds that, especially recently, technological progress has been decidedly non-neutral.

To the best of my understanding, I add to this literature (1) by being the first to reappraise and reevaluate Caselli and Coleman's findings over a larger sample of countries and dynamically over a large time period, and (2) by being the first to quantify the effects of trade on increasing a country's available technology space, and thereby decreasing its barriers to technology adoption (motivated primarily by the existing literature on the effects of trade on growth in Frankel and Romer, 1999; Feyrer, 2009a; Kee et al., 2009; Feyrer, 2009b; Arkolakis et al., 2012; Magistretti and Tabellini, 2019).

III. Data Sources and Compilation

Principally, regarding the macroeconomic variables, I rely heavily on version 9.0 of the Penn World Table, which is a massive unbalanced panel providing various measures of levels of income, output, and productivity, for a large number of countries over the period 1950-2014 (see Feenstra et al., 2015). From this dataset, I extract annual data on population, gross domestic product (GDP), and the capital stock, for 182 countries over the years 1950-2014.[3]

For constructing the skilled and unskilled labor series, I rely on four datasets. First, is the Barro-Lee Educational Attainment dataset, which provides country-level data on the percentage of the labor force with no education, some primary education, primary education completed, some secondary education, secondary education completed, some higher education, and higher education completed (see Barro and Lee, 2013). The Barro-Lee dataset contains observations every 5 years. Therefore, in order to have annual observations, I use each 5-year data point to linearly impute values for the four years in between each observation.

Then, I rely on two datasets containing estimates of mincer returns to education. First is a dataset from Caselli et al. (2015), which combines mincer coefficient estimates from a wide swath of the empirical literature, yielding a dataset of 113 countries for the years 1995 and 2005. Second is a dataset from Psacharopoulos and Patrinos (2018), which similarly collates country-level mincer estimates from a wide swath of the empirical literature, yielding unbalanced data on 121 countries with particular year estimates from 1950 to 2014. I combine these two aggregate datasets to produce a single dataset of mincer estimates for 138 countries over the years 1950 to 2014. Where there is a datapoint estimate from both sources for a specific country in a specific year, I take the average. I annually fill forward the estimates for each country so that the mincer return is assumed to be constant across years within a country until there is a newer datapoint estimate.[4]

Finally, I use an unpublished dataset from Barro-Lee that reports the duration in years for primary and secondary education for 146 countries over the period 1950-2010, at 5 year

[3] I first exclude three countries from my analysis - Qatar, Kuwait, and the United Arab Emirates - due to concerns regarding data quality and availability, late entry into the sample, and being heavy oil-driven export economies with initial low populations.
[4] I further exclude three countries from my analysis - Hungary, Slovakia, and Kyrgyzstan - due to concerns regarding schooling and mincer data quality and availability, late entry into the sample, and implausibly large implied labor stocks.

intervals. Similar to the treatment of the mincer returns data, I annually fill forward the school duration estimates for each country between observations.

IV. An Updated *"World Technology Frontier"*

A. The Aggregate Production Function

Generally, a Cobb-Douglas specification representing the aggregate production of an economy takes the form

$$y = k^{\alpha}(Ah)^{1-\alpha} \tag{1}$$

where *y* is GDP per capita, *k* is capital per capita, *h* is human capital per capita, *A* is TFP, and α is the capital share of income. While informative, this aggregate specification makes some simplifying assumptions - two of particular interest here being the supposition of a single multiplicative technology and the perfect substitutability within factor aggregates. Regarding the former, the implication is that a single factor efficiency term can sufficiently and accurately represent diverse technical efficiencies across countries (and across time). While a plausible simplification, this implies that the individual efficiencies of different factors are perfectly positively correlated. Regarding the latter assumption, the implication is that workers with different education and skill levels are assumed to be perfectly substitutable factors of production. At first glance, this simplification appears incorrect, as certain aspects of production can only be performed by workers with a particular skill-level. Moreover, this assumption contradicts empirical estimates of the elasticity of substitution between workers of different skill levels (see Katz and Murphy, 1992; Autor et al., 1998; Ciccone and Peri, 2005, among many others).

In their paper, Caselli and Coleman (2006) consider an aggregate production function specification where the assumption of perfect substitutability of labor is relaxed, and where separate efficiency terms are included for each labor type, allowing for comparative assessments of the relative efficiencies of labor types. They consider, as will I, the functional form

$$y = k^{\alpha}[\,(A_u L_u)^{\sigma} + (A_s L_s)^{\sigma}]^{\frac{1-\alpha}{\sigma}} \tag{2}$$

where *y* is GDP per capita, *k* is capital per capita, L_u is the unskilled labor aggregate, A_u is the efficiency of unskilled labor, L_s is the skilled labor aggregate, A_s is the efficiency of skilled labor, α is the capital share of income, and σ governs the substitutability between skilled and unskilled labor such that $\frac{1}{1-\sigma}$ is the elasticity of substitution. When $\sigma = 1$, the elasticity of substitution $\frac{1}{1-\sigma} \to \infty$, which is the case of perfect substitution. When $0 < \sigma < 1$, the elasticity of substitution is some finite $\frac{1}{1-\sigma} > 1$, and unskilled and skilled labor are imperfect substitutes, as is found in the empirical literature.

Of primary interest are a country's specific technology choices A_u and A_s, which vary across country and across time. In order to solve for these two unknowns, I assume that factors of production are paid their marginal product. Therefore, I can write the ratio of wages (that is, the skilled wage premium) as[5]

$$(3) \qquad \frac{w_s}{w_u} = \left(\frac{A_s}{A_u}\right)^{\sigma} \left(\frac{L_s}{L_u}\right)^{\sigma-1}$$

Using equations (2) and (3), I can back out and solve for A_u and A_s. Particularly, these two unknowns of interest have the closed form solutions[6]

$$(4) \qquad A_u = \frac{y^{\frac{1}{1-\alpha}} k^{\frac{-\alpha}{1-\alpha}}}{L_u} \left(\frac{w_u L_u}{w_u L_u + w_s L_s}\right)^{\frac{1}{\sigma}}$$

$$(5) \qquad A_s = \frac{y^{\frac{1}{1-\alpha}} k^{\frac{-\alpha}{1-\alpha}}}{L_s} \left(\frac{w_s L_s}{w_u L_u + w_s L_s}\right)^{\frac{1}{\sigma}}$$

A.i. Constructing the Labor Series and Skilled Wage Premium

Following the methodology in Caselli and Coleman (2006), I construct the unskilled and skilled labor aggregates as follows. The labor aggregates are partitioned into un- skilled and skilled according to a heuristic "literacy threshold" - that is, unskilled labor are workers who have not completed a primary education, and skilled labor are workers with any capacity above having completed a primary education. As in Caselli and Coleman (2006) and indeed as is the convention in the literature, subgroups within the aggregates are weighted by relative wages, interpreted as their relative efficiency units. Concretely, where β is the country and year specific mincer coefficient, the unskilled labor aggregate in no education equivalents is

$$(6) \qquad L_u = \text{no education} + \left[\exp\left(\beta * \frac{\text{primary years}}{2}\right) \cdot \text{some primary}\right]$$

Similarly, the skilled labor aggregate in primary education completed equivalents is

$$\begin{aligned}(7) \qquad L_s = \text{primary completed } &+ \left[\exp\left(\beta * \frac{\text{secondary years}}{2}\right) \cdot \text{some secondary}\right] \\ &+ [\exp(\beta * \text{secondary years}) \cdot \text{secondary completed}] \\ &+ \left[\exp\left(\beta * \left(\text{secondary years} + \frac{\text{higher years}}{2}\right)\right) \cdot \text{some higher}\right] \\ &+ \left[\exp\left(\beta * (\text{secondary years} + \text{higher years})\right) \cdot \text{higher completed}\right]\end{aligned}$$

As in Caselli and Coleman (2006), I apply a rescaling factor to the skilled labor aggregate to account for variation in the duration of primary schooling across countries. Thusly, multiplying L_s by $\exp[\beta(\text{primary school duration} - 4)]$ converts it to a more cross-country comparable 4-years-of-schooling equivalents.

[5] For the derivation, see Appendix A.
[6] For the derivation, see Appendix B.

Following the methodology in Caselli and Coleman (2006), I construct the relative skilled wage premium as follows. Given that the mincer coefficient represents the percentage increase in wage from an additional year of schooling, and that the unskilled labor aggregate is in no schooling equivalents and the skilled labor aggregate is in 4-years of schooling equivalents, I can define the wage ratio as $w_s/w_u = \exp(\beta \cdot 4)$.

A.ii. Summary Statistics and Stylized Facts

Table 1: Summary Statistics of Key Variables

Statistic	Mean	St. Dev.	Min	Max
y	11,610.84	12,810.94	381.78	142,924.20
k	40,931.31	49,556.82	425.20	312,756.90
L_s	93.20	75.61	1.14	1,073.91
L_u	58.55	29.91	0.00	157.26
w_s/w_u	1.47	0.34	1.03	4.11

Table 1 reports summary statistics on key variables of interest. Given the breadth of my sample, I observe considerable variation over time and over entity of most of my variables of interest. Table 2 shows the correlation matrix of key variables of interest. Generally, the results from this correlation matrix are unsurprising. Capital per capita is positively related with GDP per capita; the skilled labor endowment is positively related with GDP per capita; the unskilled labor endowment is negatively related with GDP per capita. Noteworthy for the analysis to follow is the slight negative (and statistically insignificant) relations between the skilled wage premium and GDP per capita, and the slightly positive (and also statistically insignificant) relations between the skilled wage premium and both skilled labor and unskilled labor. Given that I have amassed a valuable set of panel data, it is worth shortly exploring and presenting the evolution of these key variables of interest over time.

Table 2: Correlation Matrix of Key Variables

	$\log(y)$	$\log(k)$	$\log(L_s)$	$\log(L_u)$	$\log(w_s/w_u)$
$\log(y)$	1.00				
$\log(k)$	0.92	1			
$\log(L_s)$	0.67	0.65	1		
$\log(L_u)$	-0.65	-0.63	-0.61	1	
$\log(w_s/w_u)$	-0.12	-0.07	0.25	0.29	1

Figure 1 plots the GDP per capita of countries by region over time and paints a predictable picture. North America and Europe & Central Asia have the highest GDP per capita and have grown at relatively constant rates over the past 70 years. East Asia & Pacific experience muted growth until the 1980's, but since then display an impressive growth path. Growth in the Middle East & North Africa is somewhat stagnant and unimpressive. Likewise, growth in Latin America & Caribbean is lackluster, but has improved somewhat since the 2000's, driven by some well-performing countries. Similarly, growth in South Asia has been muted, but has improved since the 1990's, driven mostly by the growth in India. Lastly, GDP per capita in Sub-Saharan Africa has been essentially flat with very limited welfare improvements.

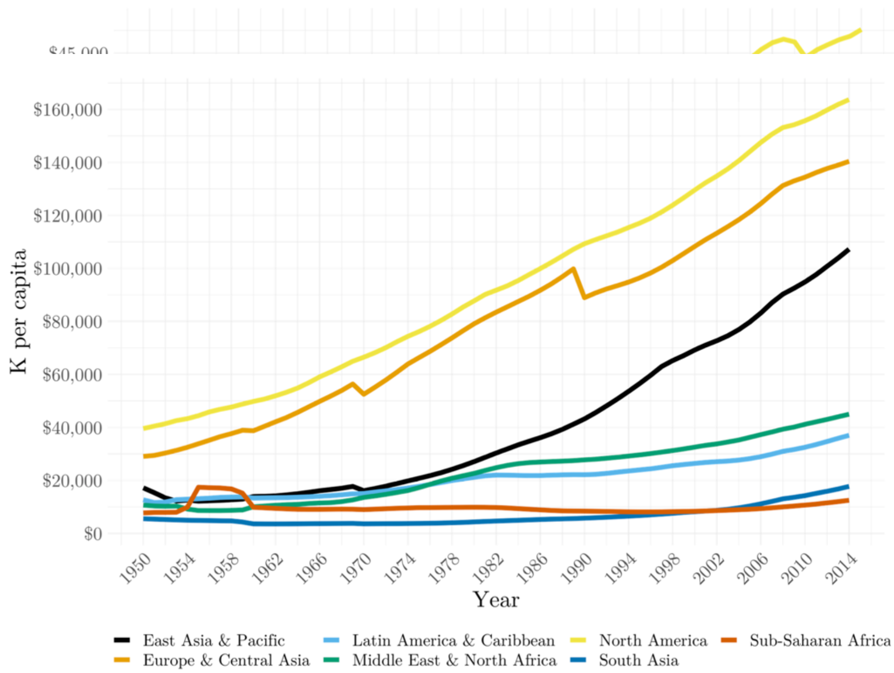


Figure 2: Capital per capita by region over time

Figure 2 plots capital per capita over time. The trends seen here broadly mirror those in Figure 1.

Figure 3 plots the ratio of skilled to unskilled labor. Skilled labor is more abundant by large factors in both North America and Europe & Central Asia, but there has been some comparatively smaller increases in the relative abundance of skilled labor notably in the Middle East & North Africa, East Asia & Pacific, and to a lesser extent Latin America & Caribbean. The relative abundance of skilled labor remains the lowest in South Asia and Sub-Saharan Africa.

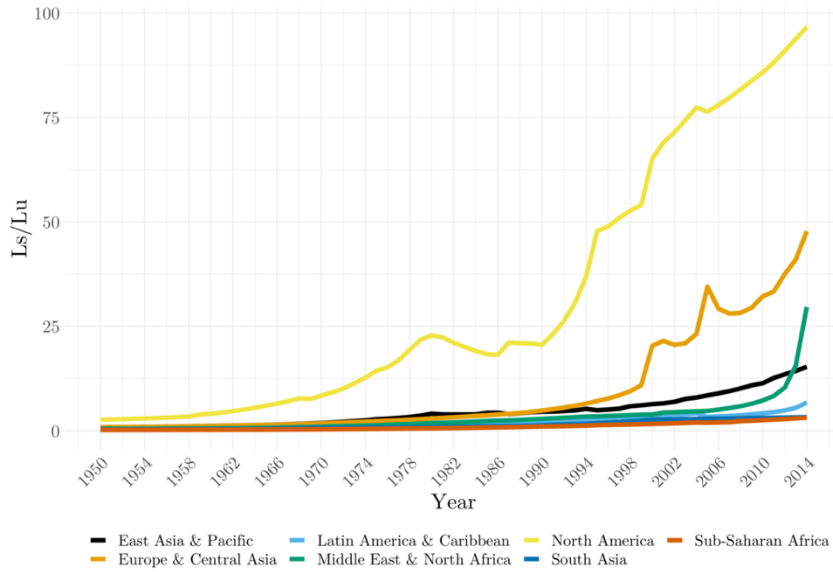


Figure 3: Ratio of Skilled to Unskilled Labor by region over time

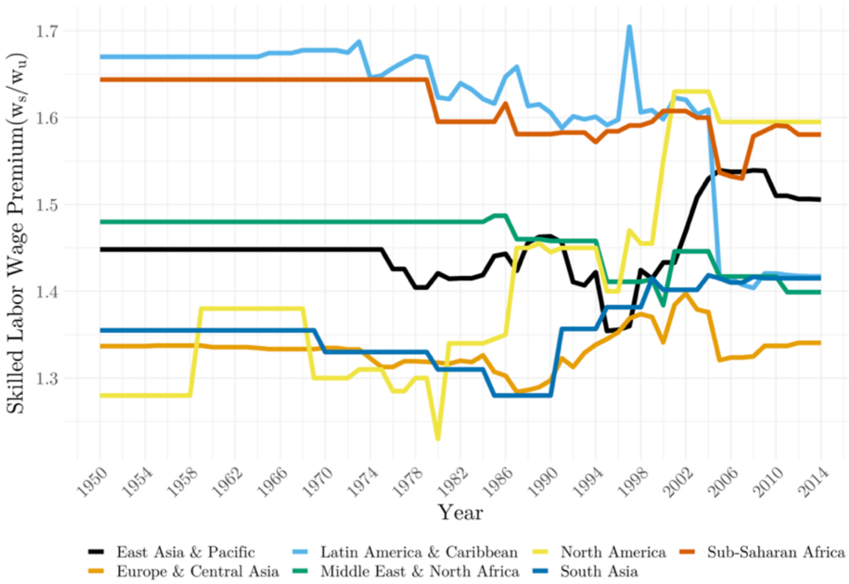


Figure 4: Wage Ratio by region over time

Lastly, Figure 4 plots the evolution of the constructed skilled labor wage premium. In the beginning, relatively skilled-labor abundant regions have relatively low skilled wage premiums. Conversely, relatively unskilled-labor abundant regions have relatively high skilled wage premiums. Overtime however, the evolution of the skilled labor wage premium appears rather idiosyncratic, and it is difficult to make any substantive generalizations when trying to reconcile the evolution of the skilled wage premium vis-à-vis the evolution of the relative abundance of skilled labor.

A.iii. Selecting Model Parameters

In order to solve for a country's skilled and unskilled labor efficiencies, the two model parameters - the capital share of income α and the elasticity of substitution $\frac{1}{1-\sigma}$ – need to be assigned plausible values. As is standard in the literature, I set the capital share of income $\alpha = 1/3$ (see Hall and Jones, 1999; Aiyar and Feyrer, 2002). Following Caselli and Coleman (2006), I set the elasticity of substitution between skilled and unskilled labor $\frac{1}{1-\sigma} = 1.4$ (that is, $\sigma \approx 0.286$) so that the two labor types are imperfect substitutes (see Katz and Murphy, 1992; Autor et al., 1998; Ciccone and Peri, 2005).

B. Preliminary Analysis

Using equations (4) and (5) I solve for my two unknowns, unskilled labor efficiency and skilled labor efficiency, for each country *i* in each year *t*. Following Caselli and Coleman (2006), when a percent increase in GDP per capita is associated with a larger increase in skilled labor efficiency than unskilled labor efficiency, I call this evidence of a *relative* skill bias in cross-country technology differences. Conversely, when a percent increase in GDP per capita is associated with an increase in skilled labor efficiency but is also associated with a decrease in unskilled labor efficiency, I call this evidence of an *absolute* skill bias in cross-country technology differences.

I perform multiple effective cross-sectional regressions of log(A_s) on log(y) (equation (8)) and of log(A_u) on log(y) (equation (9)) for all countries *i* in each time period *t* in order to get yearly estimates of the respective coefficients on log(y).

(8) $$\log\left(A_{s,i}\right) = \rho_0 + \rho_1 \log(y_i) + \varepsilon_i \text{ for each } t = 1950, \ldots, 2014$$

(9) $$\log\left(A_{u,i}\right) = \lambda_0 + \lambda_1 \log(y_i) + \varepsilon_i \text{ for each } t = 1950, \ldots, 2014$$

Given that both the dependent and independent variables are log transformed, I can interpret the resultant coefficient as the percent increase that is associated with a 1% increase in *y*. If $\rho_1 > \lambda_1 \geq 0$, then a 1% increase in *y* is associated with a relatively larger percent increase in A_s compared to A_u – that is, the *relative* skill bias. If $\rho_1 > 0$ while $\lambda_1 < 0$, then a 1% increase in *y* is associated with an increase in A_s and a decrease in A_u – that is, the *absolute* skill bias.

Figures 5 and 6 plot the coefficient estimates of ρ_1 and λ_1 from estimating the regression equations (8) and (9) over time, respectively. We can see that the ρ_1 coefficient from the A_s regression is always larger than the λ_1 coefficient from the A_u regression - that is, that a 1%

increase in GDP per capita is associated with a larger increase in A_s than in A_u across my entire sample. Throughout the entire sample, the ρ_1 coefficient from the A_s regression is positive and statistically significantly different from 0 at the 5% significance level, although its magnitude is generally decreasing over time (especially nearly monotonically so since the mid 1960's). The λ_1 coefficient from the A_u regression is not statistically significantly different from 0 at the 5% level from 1950 to approximately 1990. From 1990 onwards, the λ_1 coefficient becomes negative and statistically significantly different from 0 at the 5% level and increases in magnitude, become more negative, over the remaining time period.

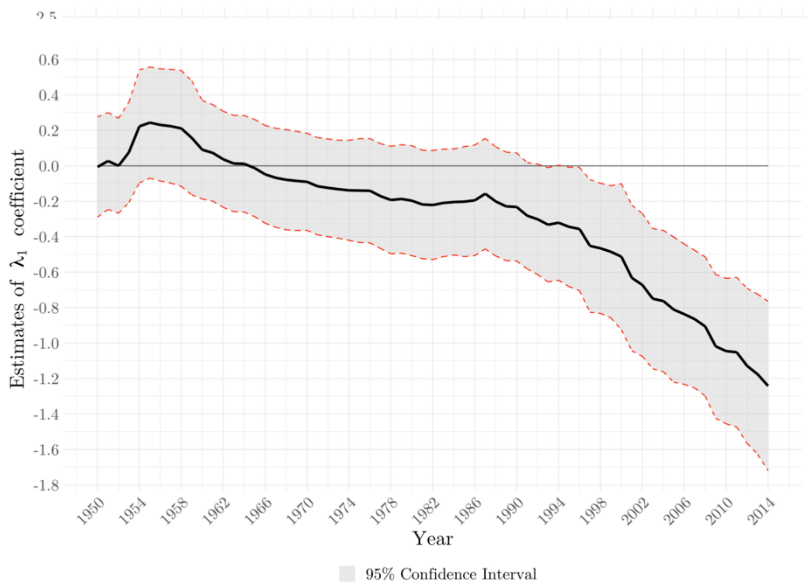


Figure 6: λ_1 estimates over time

I conclude that, up to 1990, there is persistent evidence of a relative skill bias in cross- country technology differences in my sample. From 1991 onwards, there is persistent evidence of an absolute skill bias in cross country technology differences in my sample, as the ρ_1 coefficient remains positive (albeit moderately attenuated in magnitude), and as the λ_1 becomes significantly negative. By way of this analysis, I can confirm the skill bias findings in Caselli and Coleman (2006) that, contrary to the implications of the single TFP framework, richer countries do not simply use all inputs more effectively and poorer countries do not simply use all inputs less effectively. Rather, the empirical evidence suggests that richer countries use skilled labor at least relatively more efficiently than poorer countries, and that poorer countries use unskilled labor at least relatively more efficiently than richer countries.

B.i. Deconstructing the Skill Bias Result

What generates the observed skill bias results in cross-country technology differences? Given how this specification is closed, it is the case that A_s/A_u is determined by equation (3). This is to say that my calculated values of A_s and A_u arise from the theoretical assumption that factors of production are paid their marginal product, and are therefore determined by the observed wage ratio and the observed labor endowments.

For tractability, consider the log-transformed version of equation (3)

(10) $\log\left(\frac{w_s}{w_u}\right) = \sigma \log\left(\frac{A_s}{A_u}\right) + (\sigma - 1)\log\left(\frac{L_s}{L_u}\right)$

For any fixed A_s/A_u, the relationship between L_s/L_u and w_s/w_u is negative, as countries with more skilled labor have a lower skilled-wage premium, and conversely countries with less skilled labor have a higher skilled-wage premium. Indeed, the theoretical model predicts a strong negative relationship between L_s/L_u and w_s/w_u (specifically, with my value of $\sigma = 0.286$, the slope of the line is -0.714 in log-space). Figure 7 plots this implied theoretical relationship.

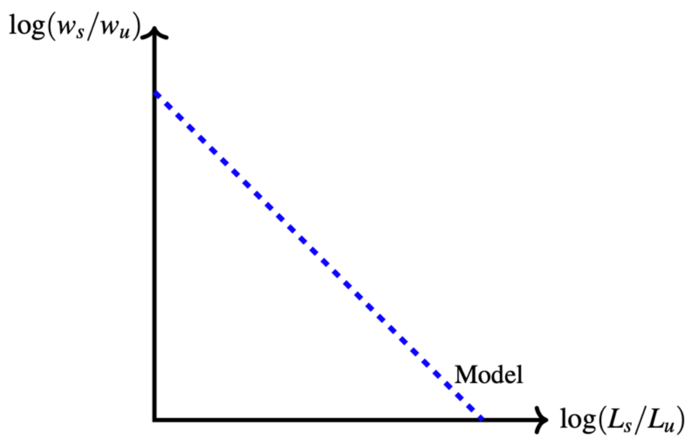


Figure 7: Theoretical Relationship between relative wages and relative labor supplies

To evaluate this theoretical prediction, I estimate effective cross-sectional regressions for each year in my sample of the form

(11) $\log\left(\frac{w_{s,i}}{w_{u,i}}\right) = \phi_0 + \phi_1 \log\left(\frac{L_{s,i}}{L_{u,i}}\right) + \varepsilon$ for each $t = 1950, \ldots, 2014$

Figure 8 plots the estimates of the ϕ_1 coefficient over time. One can see that the estimated relationship between relative wages and relative labor supplies is strictly flat - that is to say, the ϕ_1 coefficient is never statistically significantly different from 0 at the 5% level at any point in time over my sample.

Therefore, we are faced with a situation where the theoretical model predicts a strong negative relationship between relative wages and relative labor endowments, yet the data shows effectively no strong relation. For tractability, this reality is depicted in Figure 9.

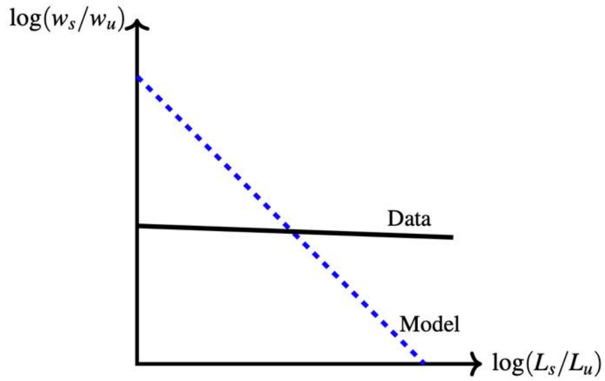


Figure 9: Theoretical and Observed Relationships between relative Wages and relative Labor Supplies

Figure 8: ϕ_1 estimates over time

Following Caselli and Coleman (2006), so as to resolve the disjunction between the theoretically predicted relationship and the observed empirical relationship illustrated in Figure 9, it must be the case that L_s/L_u and A_s/A_u are systemically positively related - that is, countries with a relatively high endowment of skilled labor L_s/L_u also have a high relative skilled labor efficiency A_s/A_u, and conversely that countries with a relatively low endowment of skilled labor L_s/L_u also have a low relative skilled labor efficiency A_s/A_u.

In congruence with Caselli and Coleman (2006), we can now see the sources and patterns of the persistent skill bias evident in my data. As described above, L_s/L_u and A_s/A_u must be systematically positively related. From Table 2, we can surmise that L_s/L_u is positively related with GDP per capita *y*. From the estimated coefficients in equations (8) and (9) presented in Figures 5 and 6 respectively, we can surmise that A_s/A_u is positively related with GDP per capita *y*. Conclusively, wealthier countries have higher relative skilled labor endowments and use skilled labor relatively more efficiently, and conversely poorer countries have relatively high unskilled labor endowments use unskilled labor relatively more efficiently. While the TFP approach posits a single multiplicative technical efficiency which is empirically positively related to GDP per capita, using data on skilled wage premiums and constructed indices of labor supplies, I show and conclude that this is not the case. Rather, countries at different income levels are more or less technically efficient at using their factors of production, and this efficiency is related to the relative abundance of the factor of production.

C. The Model of Technology Choices

How can we rationalize a country's technology choice of a specific A_u and A_s? In order to provide an economic explanation for the aforementioned pattern of technology skill bias present in my data, I employ the model proposed by Caselli and Coleman (2006) which incorporates both an endogenous "appropriate choice" feature and a frictional "barriers to technological adoption" feature. The appropriate choice aspect emphasizes the endogenous relationship between technology choice and factor endowments, and the barriers to adoption aspect focuses on the plausible cross-country (and cross-time) variation in the capacity of countries to adopt and employ new technologies.

In each country at each point in time, firms choose not only the amount of skilled and unskilled labor to use, but also choose a particular production method to employ the skilled and unskilled labor. The set of available production methods is characterized by all possible choice pairs of the technologies (A_u, A_s). From all possible choice pairs of the technologies, I restrict attention to those which are non-dominated by supposing that no rational actor would choose a technology pair (A_u, A_s) when there exists another possible pair (A'_u, A'_s) such that $A'_u > A_u$ and $A'_s > A_s$. This set of non-dominated technology choices is the country's *technology frontier*. Such a frontier space is illustrated in Figure 10, where the *x*-axis measures the efficiency of unskilled labor A_u and the *y*-axis measures the efficiency of skilled labor A_s, where Country *A* and Country *B* have different technology frontiers, and where C_a and C'_a represent particular technology pair choices for Country *A* and where C_b and C'_b represent particular technology pair choices for Country *B*.

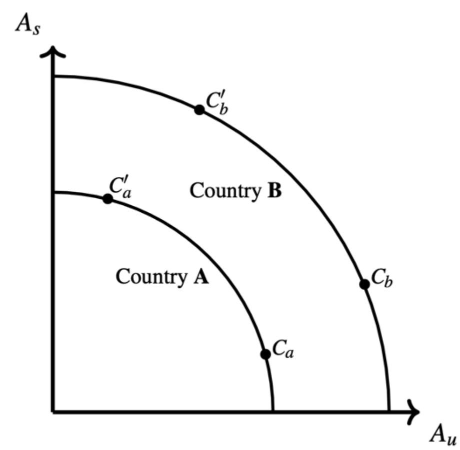
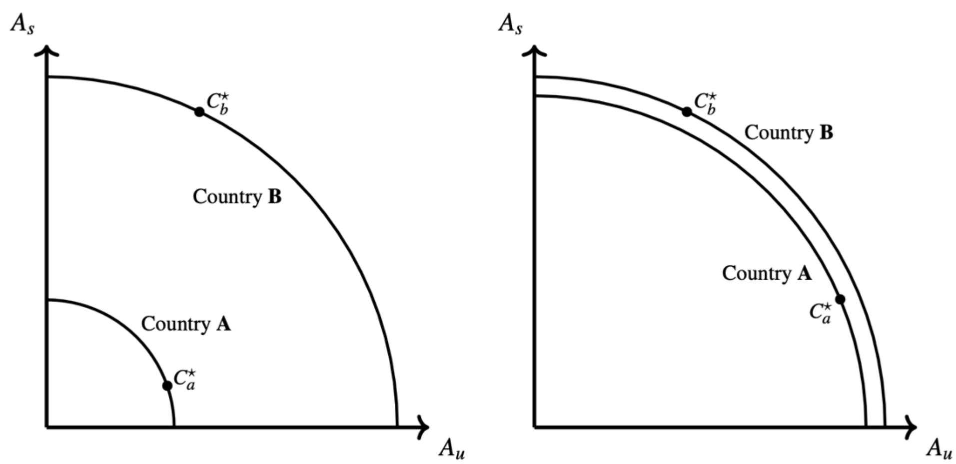


Figure 10: Illustrative Technology Frontiers

For a rational firm, the profit-maximizing production technology pair depends on the choice of factor inputs, which in turn depends on factor prices, which in turn depends on the relative available supply of the factors of production. Therefore, given that countries vary in the relative abundance of the factors of production, they will ultimately vary in the profit-maximizing technology pair choice (this can be seen in the aforementioned positive relation between L_s/L_u and A_s/A_u). Therefore, *where* along a country's specific non-dominated technology frontier the optimal choice lies depends on the country's particular relative labor endowments (that is, the "appropriate choice" aspect). For example, in Figure 10, suppose that Country *A* is relatively unskilled-labor abundant - then, we can expect an optimal technology pair choice to consist of relatively more unskilled-labor augmenting technology, such as point C_a. Conversely, suppose that Country *A* is relatively skilled-labor abundant - then we can expect an optimal technology pair choice to consist of relatively more skilled-labor augmenting technology, such as C'_a.

By allowing technology frontiers to be country specific, we suppose that the set of possible technology pairs accessible to each country varies. The size of a country's available technology space from which it can choose is determined by its ability to access and employ new technology (that is, the "barriers to technology adoption" aspect). Therefore, *where* in the $A_u - A_s$ space a country's technology frontier lies with respect to the origin is inversely related to the amount of barriers to technology adoption it experiences. As illustrated in Figure 10, in this model, Country *B* experiences fewer barriers to adoption vis-à-vis Country *A*.

Employing a model which combines the aforementioned appropriate choice aspect and barriers to adoption aspect allows me to mechanistically rationalize the persistent skill bias in cross-country technology differences seen across country and across time. In understanding how these two mechanisms interact, consider Figure 11. Assume that Country *A* is poor and relatively unskilled-labor abundant, and Country *B* is wealthy and relatively skilled-labor abundant. When the technology frontiers are sufficiently far away as in Figure 11(a), the barriers to adoption effect will dominate, and the optimal technology choice pair for Country *B*, $C_b^\star$ will display an absolutely higher level of both the unskilled and skilled labor technologies A_u and A_s vis-à-vis the optimal technology choice pair for Country *A*, $C_a^\star$ (that is, a case of *relative* skill bias). When the technology frontiers are sufficient close as in Figure 11(b), the appropriate choice effect will dominate, and we will observe in Country *B*'s optimal choice $C_b^\star$ a higher level of the skilled labor technology A_s and we will observe in Country *A*'s optimal technology choice $C_a^\star$ a higher level of the unskilled labor technology A_u (that is, a case of *absolute* skill bias).



(a) Barriers to adoption dominates. (b) Appropriate technology choice dominates.

Figure 11: Barriers to Adoption Effect *vs.* Appropriate Choice Effect

Following Caselli and Coleman (2006), for each country in each year, the economy is characterized by a larger number of competitive firms. Firms employ unskilled labor L_u, skilled labor L_s, and capital k. Firms are price-takers regarding the wage rate of unskilled labor w_u, the wage rate of skilled labor w_s, and the rental rate of capital r. As Caselli and Coleman (2006) illustrate, the novel element of the model at hand is the assumption that in addition to choosing the factor inputs, firms also choose the production technologies (A_u, A_s) from the set of feasible technologies available in that country in that year. They represent, as will I, the technology frontier with the functional form

$$(12) \qquad (A_s)^{\omega} + \gamma(A_u)^{\omega} \leq B$$

where parameters $\omega > 0$ and $\gamma > 0$ dictate the curvature and trade-off between A_s and A_u, and $B > 0$ represents the 'height' of a particular frontier.

For tractability, we can succinctly conceptualize the representative firms' problem for each country *i* in each year *t*, as the following profit maximization problem subject to the technology frontier constraint:

$$(13) \qquad \pi(w_u, w_s, r) = \max_{L_u, L_s, k, A_u, A_s} k^{\alpha} \left[(A_u L_u)^{\sigma} + (A_s L_s)^{\sigma}\right]^{\frac{1-\alpha}{\sigma}} - w_u L_u - w_s L_s - rk$$

$$\text{s.t. } (A_s)^{\omega} + \gamma(A_u)^{\omega} \leq B$$

D. Technology Frontiers

D.i. Backing out the Parameters

Following Caselli and Coleman (2006), I solve for the ω, γ, and *B* parameters which characterize the technology frontier that rationalizes a country's implied choice pair of A_s and A_u. The γ and *B* parameters are country and year specific. The curvature parameter ω is left to be constant across all countries in a given year, but can vary from year to year.

Specifically, I make use of the firms first-order condition with respect to *Au* which at optimum, reduces to[7]

$$(14) \qquad \left(\frac{A_s}{A_u}\right)^{\omega-\sigma} = \gamma\left(\frac{L_s}{L_u}\right)^{\sigma}$$

I can rewrite equation (14) log-transformed in order to perform effective cross-sectional regressions for all countries *i* in each time period *t*

$$(15) \qquad \log\left(\frac{A_{s,i}}{A_{u,i}}\right) = \frac{1}{\omega-\sigma}\log(\gamma_i) + \frac{\sigma}{\omega-\sigma}\log\left(\frac{L_{s,i}}{L_{u,i}}\right) \quad \text{for each} \quad t = 1950, \ldots, 2014$$

Using equation (15), I regress $log(A_{s,i}/A_{u,i})$ on $log(L_{s,i}/L_{u,i})$ for each time period *t*. Then, given the coefficient estimate on $log(L_{s,i}/L_{u,i})$ and my calibrated value of $\sigma \approx 0.286$, I back out the value of ω annually for each year *t*. Then, using the regression residual, I recover the implied value of γ for each country *i* in each year *t*. Finally, with estimates of ω and γ and a country's choice of A_u and A_s, using equation (12), I back out *B* for each country *i* in each year *t*.

[7] For the derivation, see Appendix C.

D.ii. Frontier Parameter Summary Statistics

Table 3 presents summary statistics of the ω, γ, and *B* parameters just calculated.

Table 3: Summary Statistics of Parameters

Statistic	Mean	St. Dev.	Min	Max
ω	0.40	0.003	0.40	0.41
γ	1.00	0.08	0.85	1.48
B	4.01	1.62	1.17	14.76

Of particular note, my estimate of ω is nearly identical to the estimate of 0.41 calculated from the single cross-section used in Caselli and Coleman (2006), and is constant and well bounded across my sample from year to year. Additionally, the frontier height parameter *B* has a significantly large range over my sample across countries and across time (an observation of particular importance to the following section on the evolution of technology frontiers).

D.iii. Frontiers and Their Evolution

To explore how technology frontiers evolved over time, I first employ the frontier height parameter *B* as an indicative measure. To this end, Figure 12 plots average heights of frontiers by region over time.

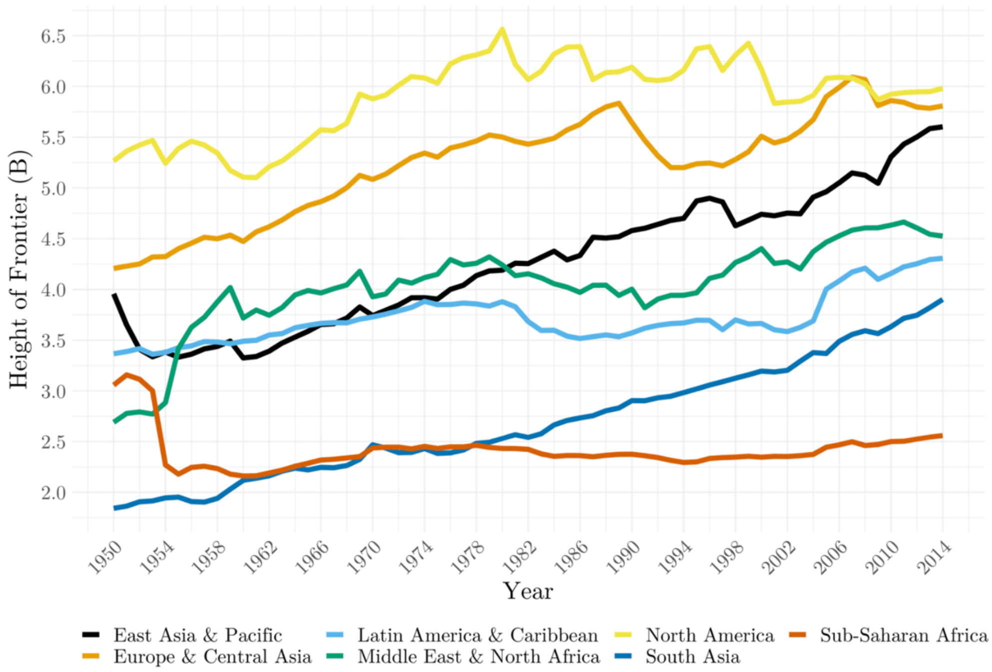


Figure 12: Average frontier heights by region over time

Generally, the picture of economic progress and growth patterns that Figure 12 paints is expected. North America has had the highest frontiers on average across the entire time period, with Europe & Central Asia closely following throughout. Both South Asia and East Asia & Pacific have experienced the most clear frontier growth and expansion, especially since the 1980's. The Middle East & North Africa and Latin America & the Caribbean have experienced very moderate frontier expansion, but have remained more or less stagnant especially from the 1970's to the 2000's. Lastly, Sub-Saharan Africa has been essentially flat, exhibiting no significant technology frontier growth and expansion, over the entire time period.

Further, as a starting point of comparison of technology frontiers, using my data I replicate in Figure 13 a central figure in the Caselli and Coleman (2006) paper, which features the scatter plot space of $log(A_u)$ and $log(A_s)$ and plots the technology frontier equations of three representative countries - Italy, Argentina, and India - for their single cross-sectional year 1988. The conclusions they draw in their analysis are analogous to the conclusions I can draw here. A poorer country, such as India, operates on a frontier that is significantly inside that of a wealthier country, such as Italy, and a more 'middle-income' country such as Argentina operates on a technology frontier in between the high-income and low-income countries. Importantly, here in Figure 13, one can concretely visualize how the appropriate choice and barriers to adoption margins of technological choice nest together. At a specific point in time, a country's technology pair choice of a specific (A_u, A_s) is an endogenous result determined by their endowments of unskilled labor and skilled labor, chosen to augment the relatively more abundant factor - that is, the appropriate choice margin. But of course, this appropriate technology choice arises from, and is conditional on, a particular technology space and set of feasible technology choices - that is, the barriers to adoption margin. We can see in Figure 13 that poorer countries consistently have lower technology frontiers, and likewise smaller technology choice spaces, because they face comparatively larger barriers to technology adoption.

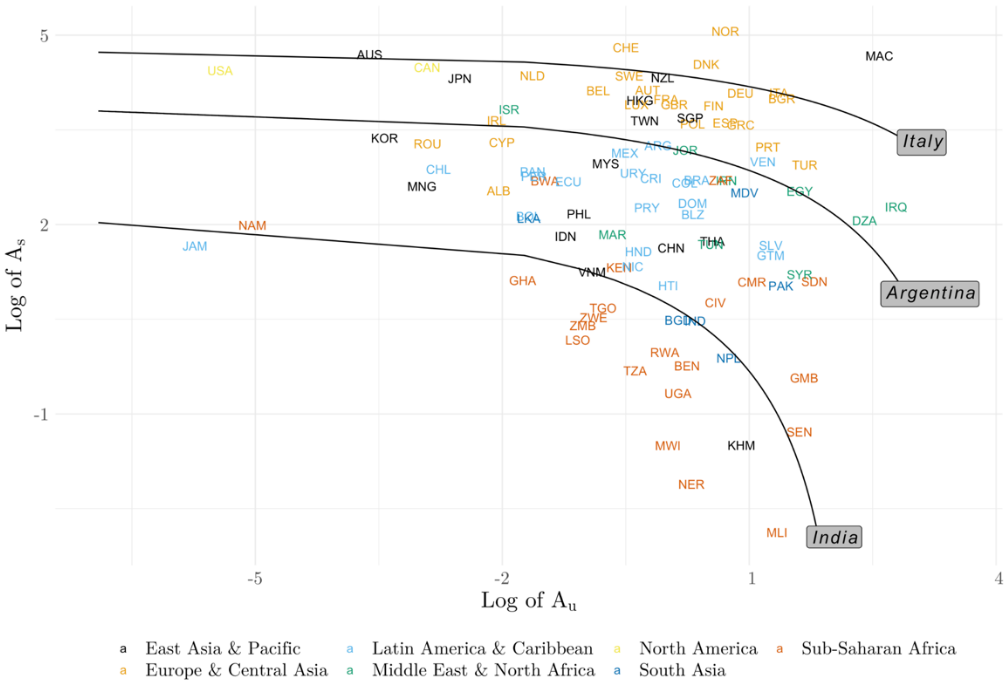
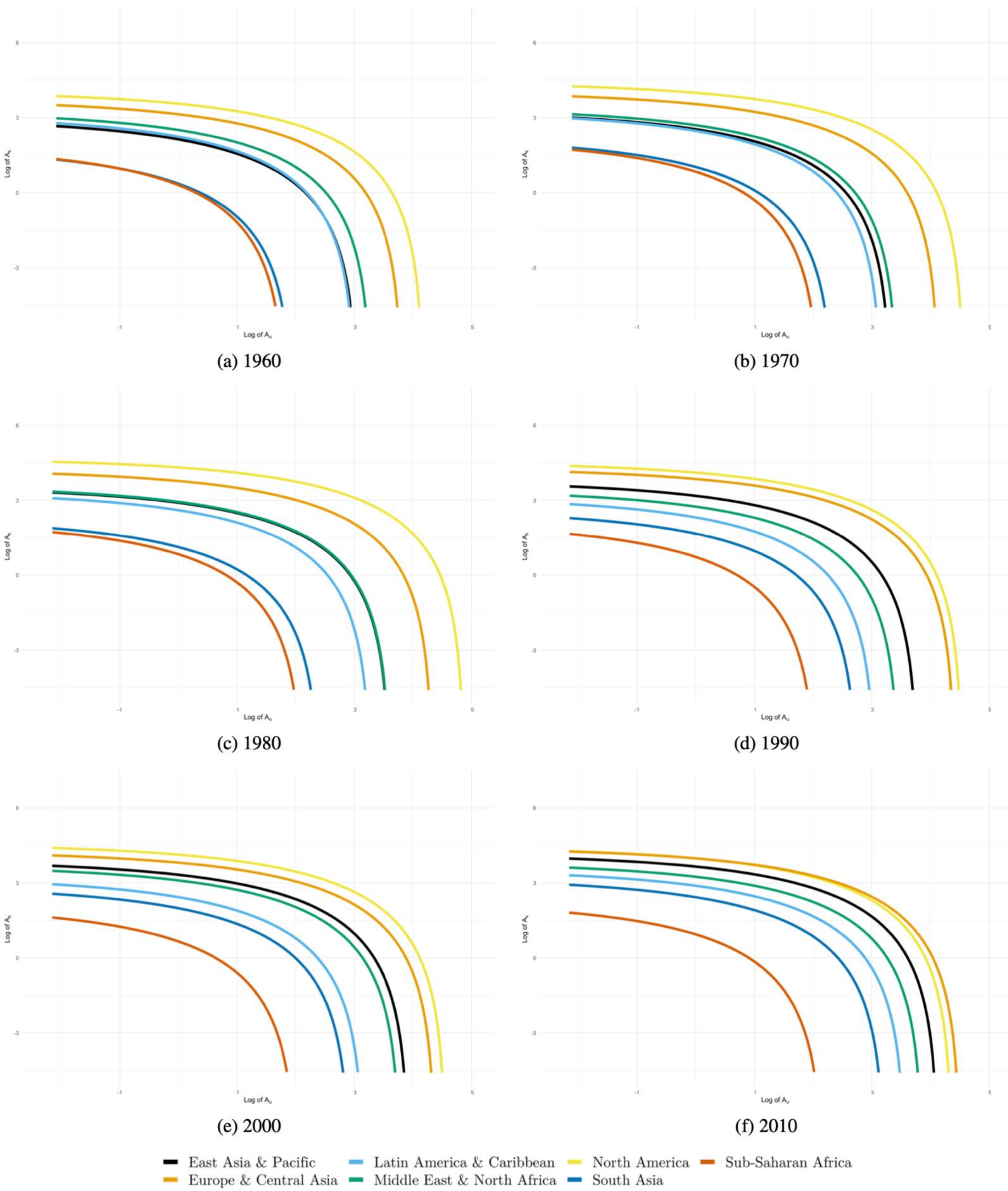


Figure 13: Country Technology Frontiers - 1988



(a) 1960

(b) 1970

(c) 1980

(d) 1990

(e) 2000

(f) 2010

Figure 14: Technology Frontier evolution by region over time

While much can be gleaned from understanding the characteristics of the global technology space from a cross-sectional view at a particular point in time, I can go beyond this. A significant advantage of my compiled dataset and approach is not only the expanded entity size, but also the time-series component. Now, I can document and evaluate not only the state of frontiers at a given point in time, but I can also highlight the evolution of frontiers *across* time. Figure 14 plots the evolution of the space of frontiers by region in decade increments from 1960 to 2010.

Generally, the picture of economic progress and growth patterns that the evolution of these frontiers paints is again expected as it broadly squares quite well with the literature and stylized facts on realized economic growth over the second half of the 20th and early 21st centuries. North America has remained at the fore of the technology frontier space, and Europe & Central Asia has progressed to obtain a roughly equivalent frontier to that of North America. Tremendous growth in the frontier space has been achieved by South Asia, especially since the 1980’s. Slightly attenuated but nevertheless substantive growth has been seen in East Asia & Pacific, again especially since the 1980’s. Some moderate frontier growth can be seen in the Middle East & North Africa, particularly from the 1990’s onward. The Latin America & Caribbean technology frontier, had been largely stable, but some modest frontier growth can be seen since the 2000’s. Lastly, the technology frontier space of Sub-Saharan Africa has remained essentially constant, experiencing no significant technology frontier expansion.

E. Robustness Checks

Here I perform some parameter robustness checks to establish the durability of my analysis and conclusions.

E.i. Variation of the Elasticity of Substitution

Following Caselli and Coleman (2006), I set $\sigma = 0.286$ so that the elasticity of substitution $\frac{1}{1-\sigma}$ between skilled and unskilled workers is 1.4, a value obtained from the estimation work in Katz and Murphy (1992). This specific elasticity estimate appears to be reasonable and in congruence with the literature - Autor et al. (1998) confirm that the elasticity is likely to be bounded between 1 and 2, settling on 1.4 as a consensus estimate; Ciccone and Peri (2005) find an elasticity ranging from 1.2 to 2, with their preferred estimate being 1.5; Autor et al. (2008) find an elasticity ranging from 1.37 to 2.48, settling on an aggregate estimate of 1.62. While this elasticity estimate seems plausible and grounded, one could be concerned that my results of persistent cross-country and cross-time skill bias are in some way driven by the particular choice of the elasticity of substitution.

To this end, I re-estimate equations (4) and (5) and back out the respective efficiency parameters A_u and A_s for a host of elasticity estimates ranging from 1.1 ($\sigma = 0.095$) to 2.5 ($\sigma = 0.6$). As the elasticity of substitution tends toward 1, skilled and unskilled labor become more imperfect substitutes, and I see progressively more substantial evidence of an *absolute* skill bias - that is, an increase in y is associated with an increase in the skilled labor efficiency, and an increase in y is associated with a decrease in the unskilled labor efficiency. As the elasticity of substitution tends toward 2.5, skilled and unskilled labor become more perfect substitutes, and I see progressively more substantial evidence of a *relative* skill bias - that is, while an increase in y is positively related to both A_s and A_u, it brings about a comparatively larger increase in A_s vis-à-vis A_u.

Nevertheless, we observe skill bias in all cases considered, and thusly on the whole, my results remain robust and my conclusions unchanged.[8]

E.ii. Heterogeneity in the Capital Share of Income

Following long-standing convention, I set the capital share of income $\alpha = 1/3$. Despite the salience of this convention, recent work has revealed considerable cross-country and cross-time variation (see Bernanke and Gurkaynak, 2001; Gollin, 2002; Caselli and Feyrer, 2007). To this end, I use data on the labor share of income from the Penn World Table to get country-year specific values of the capital share of income, i.e. for country *i* in year *t*,

$$\alpha_{i,t} = 1 - \text{Labor Share of Income}_{\ i,t} \tag{16}$$

Using these new values of $\alpha_{i,t}$, I re-estimate equations (4) and (5) and back out the respective efficiency parameters A_u and A_s. When allowing for cross-country and cross-time variation in the capital share of income, I see strong evidence of relative skill bias throughout most of my sample until the early 2000's, at which point I begin to see strong evidence of an absolute skill bias. Again, on the whole, my results remain robust and conclusions unchanged.[9]

V. Counterfactual Calculations, Development Accounting, and the Effects of Trade

As shown above, I model a country's technology choice (A_u, A_s) as arising from an aspect of appropriate technology choice and from an aspect of barriers to technology adoption. In essence, conditional on the particular state of barriers faced at the time, a country "chooses" its technology as a function of its labor endowments. Having shown above that barriers to adoption do exist, as poorer country's frontiers lie consistently within those of richer countries, and that there has been considerable movement of frontiers and elimination of barriers in certain countries and regions of the world over time, I now investigate the contribution of barriers to technology adoption on the observed disparities in economic development and the wealth of nations. Particularly, I am concerned with the possible welfare gains to be realized from the total elimination of barriers to technology adoption, and assessing trade as a plausible causal factor that leads to the elimination of these barriers.

A. The Counterfactual Removal of Barriers

What are the possible gains to be realized from the total elimination of barriers? In an attempt to quantify this, I solve for what GDP per capita county *i* in year *t* could attain if it could choose its technology pair (A_u, A_s) from the world technology frontier in that year.

This is a two step process. First, I define the novel variable "technology space" for each country in each year as the area under its technology frontier curve. Given calculated parameter estimates, I can rewrite the technology frontier equation (12) at equality as

[8] For these results, see Appendix D.
[9] For these results, see Appendix D.

(17) $$A_s = (B - \gamma A_u^{\omega})^{\frac{1}{\omega}}$$

Then, I solve for θ, which is the root of equation (17), for each country in each year, defined as

(18) $$\theta = \{A_u \in R_+ : (B - \gamma A_u^{\omega})^{\frac{1}{\omega}} = 0\}$$

Given the nature and shape of the frontier function, there exists a single real positive root, which I define as the upper limit of the integration of the technology space. Accordingly, I define the technology space for a given country in a given year as

(19) $$\text{Technology Space} = \int_0^{\theta} (B - \gamma A_u^{\omega})^{\frac{1}{\omega}} dA_u$$

which is the area under its frontier curve integrated from 0 to θ.

Second, for each year, I find the country with the largest technology space, and define its function parameters $(\omega^{\star}, \gamma^{\star}, B^{\star})$ as constituting the frontier function of the proverbial "world technology frontier" for the given year. Then, I solve the following constrained optimization problem,

(20) $$\text{Optimal GDP per capita} = \max_{A_u, A_s} \; k^{\alpha}[(A_u L_u)^{\sigma} + (A_s L_s)^{\sigma}]^{\frac{1-\alpha}{\sigma}}$$

$$\text{s.t. } A_s^{\omega^{\star}} + \gamma^{\star} A_u^{\omega^{\star}} \leq B^{\star}$$

where each country in a given year, given its labor endowments, chooses its technical efficiencies (A_u, A_s) from the world technology frontier in order to achieve the maximum possible GDP per capita.[10]

Now, I can evaluate the output gains possible if all countries had unfettered access to the world technology frontier. Figure 15 plots the possible output gain (Optimal GDP per capita / Observed GDP per capita), from the removal of all barriers to adoption for the year 1988. I choose to present the data from 1988 in order to allow me to draw comparisons between my counterfactual calculations and those presented in Caselli and Coleman (2006). Figure 15 shows that substantial output gains could be realized from the removal of barriers to technology adoption, often by factors of 10 or more in particularly poor and underdeveloped countries. My results here are in line with those in Caselli and Coleman (2006) who find possible output gains of a factor of 6 in 1988. My results are larger than those in Caselli and Coleman (2006), however this is due to my sample containing more middle- and low-income countries which were left out of their analysis, biasing their results as an effective lower-bound estimation.

Further, I can investigate how the possible output gain from the removal of barriers has evolved over time. Figure 16 plots the distributions of the output gain over my sample in 5-year increments. There are a few notable observations from this figure. First, the middle interquartile range of the gains from barrier removal are generally well bounded between factors of 2 to 8, and follow no discernible pattern over time. Second, and accordingly, the average output gain is quite

[10] For the proof that a solution to this problem exists and is unique, see Appendix E.

consistent across time, with a mean output gain factor of ≈ 6. Finally, the upper tail of the distribution of gains from removing barriers increases over time. This observation is no cause for concern and is in accordance with aforementioned stylized facts of economic progress. First, we know that the poorest countries have a relatively constant low GDP per capita and a constant low technology frontier over my sample. Second, we know that the richest countries have experienced significant growth in their GDP per capita and in their technology frontiers. Therefore, having defined the possible output gain as Optimal GDP per capita over Observed GDP per capita, we can see that for the poorest countries in my sample, the denominator (Observed GDP per capita) has remained relatively constant over time whereas the numerator (Optimal GDP per capita) has grown significantly over time, thereby explaining the widening of the distribution at the upper extreme.

B. Development Accounting

It is worth considering, in a development accounting sense, what fraction of the observed cross-country income variation can be explained by factor endowments, and what fraction is due to barriers to technology adoption. The percent of variation in cross-country income due to barriers to technology adoption can be calculated for a given year as

$$\text{\% of Variation due to Barriers} = 100 \times \left(1 - \frac{\text{sd}[\log(\text{Optimal GDP per capita})]}{\text{sd}[\log(y)]}\right) \tag{21}$$

Table 4 presents the standard deviation of the log of Observed GDP per capita y, the standard deviation of the log of Optimal GDP per capita, and the percent of variation in cross-country income due to barriers to technology adoption (as calculated according to equation (21)). While decreasing over time, barriers to technology adoption explains on average 48% of observed cross-country income variation over my sample.

Table 4: Variation in Observed and Optimal GDP per capita

	1960	1970	1980	1990	2000	2010
sd[log(y)]	0.97	1.01	1.07	1.11	1.16	1.13
sd[log(Optimal GDP)]	0.44	0.46	0.48	0.49	0.53	0.53
% of Variation due to Barriers	57.7%	53.5%	48.6%	45.8%	40.8%	41.5%

Figure 15: Possible Output Gain - 1988

Figure 16: Possible Output Gain over time

C. The Effects of Trade on Barriers to Adoption

The potential gains to welfare from reducing barriers to adoption are large, and barriers to adoption can explain a significant fraction of observed cross-country variation in GDP per capita. Given this, I now pursue a preliminary analysis evaluating the causal impact of general economic integration – as measured by trade volume – on reducing barriers to technology adoption.

C.i. Motivating Idea

Arguably the defining feature of the post-Second World War global economy has been the expansion of global trade and interconnectedness. Much research has been done evaluating the multi-faceted effects of increased international trade throughout the second half of the 20th century.

While a substantive portion of research in the literature has generally focused on the effects of trade on economic growth, here I instead hypothesize that trade has a causal impact on a country's barriers to technology adoption. Specifically, in the context of this analysis, increases in trade reduce barriers to technology adoption, increasing a country's available technology space, yielding a more efficient non-dominated appropriate technology choice given a country's factor endowments, and therefore increasing a country's income. This hypothesized model of the effects of trade is simply diagrammatically represented in Figure 17.

Figure 17: Trade Theory Flow Chart

C.ii. Methodology and Data

I wish to estimate the effect of trade on a country's technology space with an equation of the form

$$\log(\text{Technology Space}_{it}) = \zeta + \psi \times \log(\text{trade}_{it}) + \mu_i + \delta_t + \varepsilon_{it} \tag{22}$$

where Technology Space_{it} is the technology space for country *i* at time *t*, trade_{it} is the sum of bilateral trade flows for country *i* at time *t*, where μ_i are country fixed effects, where δ_t are time fixed effects, and where ε_{it} is the idiosyncratic error term. The parameter of interest is ψ, which I hypothesize to be greater than zero (i.e., an increase in trade volume increases a country's technology space). However, there is a substantial problem – equation (22) cannot be identified due the endogeneity of trade and concerns of reverse causality. Therefore, in order to estimate the effect of trade on technology space, I employ an instrumental variable strategy to address these issues of endogeneity and reverse causality.

In their influential paper, Frankel and Romer (1999) use a bilateral gravity trade flow equation to construct a particular geographic instrument for assessing the effect of trade on income. However, their instrument is time-invariant (therefore only applicable in cross-sectional analyses), and their results are not robust to controlling for time-invariant omitted variables such as distance from the equator and land area covered by tropics (see Rodriguez and Rodrik, 2001). Feyrer (2009b) also assesses the effect of trade on income during the period 1960-1995, but solves the problems of Frankel and Romer (1999) by using the exogenous heterogeneity in benefits arising from changes in the importance of air transportation vis-à-vis sea transportation to construct a time-variant geographic instrument, and can therefore use the time-series variation to control for time-invariant country fixed effects. Similarly, Pascali (2017) assesses the effect of trade on economic development during the period 1870-1913 using a time-variant geographic instrument à la Feyrer (2009b), but using the advent and evolution of steamship transportation. Magistretti and Tabellini (2019) assess the effect of trade and economic integration on democracy, and construct a time-variant geographic instrument à la Feyrer (2009b), but over a longer time-period with more recent data (1950-2015), and make technical improvements in the construction of the instrument, such as including country and year fixed effects in the bilateral gravity trade flow equation.

For my two-stage least squares instrumental variation strategy, I estimate the equations

$$\log(\text{trade}_{it}) = \chi + \tau \times \log(\text{trade instrument}_{it}) + \xi_i + \eta_t + \varepsilon_{it} \tag{23}$$

$$\log\left(\text{Technology Space}_{it}\right) = \zeta + \psi \times \log\left(\widehat{\text{trade}_{it}}\right) + \mu_i + \delta_t + \varepsilon_{it} \tag{24}$$

where equation (23) is the first stage reduced form equation of the endogenous trade variable in terms of all exogenous variables, and where equation (24) is the second stage structural equation regressing technology space on the instrumented trade values from the first stage regression.

For my instrumental variable estimation, I use the trade measure and trade instrument constructed by Magistretti and Tabellini (2019). Their observed trade measure and trade instrument data takes the form of an unbalanced panel of 212 countries for the years 1950-2015. I match their dataset with my unbalanced panel on technology space for 108 countries for the years 1950-2014 to produce a final unbalanced panel of 86 countries for the years 1950-2014. To focus on longer-term effects, I follow Feyrer (2009b) and Magistretti and Tabellini (2019) and only keep data observations at 5-year intervals, so that the final panel dataset consists of measures of technology space, trade volume, and the trade instrument for 86 countries over 13 time periods from $t = 1$ (1950) to $t = 13$ (2010).

C.iii. Instrument Relevance and Exogeneity

As previously noted, concerns of endogeneity and reverse causality reasonably abound when considering estimating the causal effect of trade on a country's technology space. These concerns inform my desire to use an instrumental variable estimation approach to isolate the exogenous component of the trade volume measure, and thusly use this exogenous component of trade to attain unbiased estimates of the effects of trade on technology space. However, a few conditions concerning the instrument must be met in order for a two-stage least squares instrumental variable estimation to be a valid and preferable approach – namely satisfying instrument relevance and instrument exogeneity. Instrument relevance is the condition that $\text{Corr}(\text{trade instrument}_{it}, \text{trade}_{it}) \neq 0$, which is to say that my instrumental variable must be strongly related to my endogenous regressor. Instrument exogeneity is the condition that $\text{Corr}(\text{trade instrument}_{it}, \varepsilon_{it}) = 0$, which is to say that my instrumental variable must be exogenous and therefore uncorrelated with the error term. If the instrumental variable has no independent effect on technology space and satisfies the instrument relevance and instrument exogeneity conditions, then I can conclude that the instrument is valid and can be used to obtain unbiased and consistent estimates of my parameter of interest, ψ.

The instrument relevance condition can be directly tested. Table 5 presents the first stage regression (equation (23)) controlling for country and time fixed effects, with standard errors

Table 5: First Stage Regression

	(1) log(trade)
log(trade instrument)	1.415***
	(0.433)
Country Fixed Effects	Yes
Time Fixed Effects	Yes
F-Stat for Weak IV's	10.70
Within R^2	0.914
Number of Observations	931
Number of Countries	86

Standard errors in parentheses are clustered at the country level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

clustered at the country level. In the first stage, we see evidence that the trade instrument appears to be relevant and valid, with the coefficient point-estimate being statistically significantly different from 0 at the 1% level. Nevertheless, even if the instrument appears to be relevant, it may still be the case that the instrument is a so-called "weak instrument." The issue of weak instruments is problematic in obtaining consistent and unbiased estimates, as small correlations between the instrument and the error term can cause large inconsistencies and bias in the parameter estimates if the instrument is also weakly related with the explanatory variable. Therefore, following the commonly used rule of thumb (see Staiger and Stock, 1997; Stock and Yogo, 2002), I report the *F*-statistic from the first stage regression in Table 5, which satisfies the rule of thumb that the instrument is not weak if $F > 10$.

However, the instrument exogeneity condition cannot be directly tested as it concerns the un-observed residual. In the case at hand, instrument exogeneity requires that the trade instrument is exogenous and uncorrelated with omitted variables, and only affects a country's technology space through trade volume. I follow the reasoning proposed in Feyrer (2009b) and Magistretti and Tabellini (2019) and posit that it is reasonable to assume exogeneity of the trade instrument. Indeed, the rise of air transport vis-à-vis sea transport is reasonably an exogenous shared technological advancement which generated heterogeneous variation that is exogenous to any particular country. As noted by Feyrer (2009b) and Magistretti and Tabellini (2019), given the plausibly exogenous trade instrument and the inclusion of country and time fixed effects afforded by the panel data, the possible non-trade channels through which the trade instrument can act on technology space are extremely limited to particular time-varying flows, such as migration and foreign direct investment (however, as will be shown, changes in population do not drastically bias the estimation of the ψ parameter). Accordingly, it may be fruitful to interpret results as an upper-bound measure of the effect of economic integration/globalization, rather than strictly trade in goods and services.

C.iv. Results

Table 6 presents the main results from the second stage regression (that is, equation (24)) controlling for country and time fixed effects, with standard errors clustered at the country level. Of primary interest is the coefficient on log(trade), significant at the 5% level, which indicates that a 1% increase in trade volume brings about approximately a 0.37% increase in technology space. The coefficient on log(trade) is greater than zero, as hypothesized, lending credence to my conjecture that an increase in trade produces a larger available technology space, and therefore constitutes an effective reduction in barriers to technology adoption. I posit these estimates are causal, unbiased, and robust. By using an instrumental variable estimation approach with a valid and exogenous instrument, I have addressed the issues of endogeneity and reverse causality. Additionally, given that I have panel data, I am able to control for country-specific time-invariant correlates (country fixed effects), and I am able to control for covariates which are constant across countries but vary over time (time fixed effects).

Table 6: Primary Results - Second Stage Regression

	(1) log(Technology Space)
log(trade)	0.370**
	(0.164)
Country Fixed Effects	Yes
Time Fixed Effects	Yes
Within R^2	0.447
Number of Observations	931
Number of Countries	86

Standard errors in parentheses are clustered at the country level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.v. Robustness Checks

I entertain a variety of alternative specifications in order to evaluate the robustness of the primary regression results presented in Table 6. To this end, Table 7 presents a host of alternative specification considerations performing the two-stage least squares estimation of equations (23) and (24).

One may be concerned that wealthy countries which trade more are driving the positive relationship identified in Table 6. To address this concern, model (1) includes only non-OECD countries. The point estimate on log(trade) is attenuated, but is still of reasonable magnitude and statistically significant at the 5% level. One may be concerned that, following the dissolution of the Soviet Union in 1991, the subsequent entrance of all post-soviet states into my data set from 1995 onwards may bias the positive result identified in Table 6. Accordingly, model (2) excludes all states which were part of the USSR. The coefficient on log(trade) is nearly identical to the primary result, and is statistically significant at the 5% level. While the primary result in Table 6 controls for country fixed effects and time fixed effects, given the breadth of my data, I can also control for omitted factors related to differential trends across regions – that is, by controlling for region-by-time fixed effects. To this end, using the full sample of countries, model (3) includes region-by-time fixed effects. The coefficient on log(trade) is attenuated, but still of relevant magnitude and statistically significant at the 10% level. Finally, again using the full sample of countries and including region-by-time fixed effects, model (4) adds the additional control variable of the change in (log) population level (population data is from the Penn World Table (see Feenstra et al., 2015)). While the change in population enters significantly into the specification, the coefficient on log(trade) is nearly unchanged compared to the estimate in Table 6 and is statistically significant at the 10% level.

For a considerable number of countries towards the beginning of my sample, the constructed trade instrumental variable takes the value of 0. This means that, when log transformed, the observation is dropped from my regression analysis as log(0) is undefined. To this end, I present two alternative transformations to the simple log transformation in an attempt to recover and utilize these lost observations in my regression analysis. Models (5) and (6) present the case where the instrumental variable (IV) takes on the transformation log(IV + 1). Model (5) includes only country and time fixed effects, whereas model (6) adds region-by-time fixed effects and the change in (log) population. Again, the coefficient estimates are not drastically different and are still statistically significant. Models (7) and (8) present the case where the instrumental variable takes on the inverse hyperbolic sine transformation IHS(IV).[11] Model (7) includes only country and time fixed effects, whereas model (8) adds region-by-time fixed effects and the change in (log) population. Once again, the coefficient estimates are not drastically different and are still statistically significant.

[11] That is: $\mathrm{IHS}(\mathrm{IV}) = \mathrm{arsinh}(\mathrm{IV}) = \log\left(\mathrm{IV} + \sqrt{\mathrm{IV}^2 + 1}\right)$, (see Burbidge et al., 1988).

Table 7: Robustness Checks

	(1) No OECD	(2) No USSR	(3) Full Sample (R×T FE)	(4) Full Sample (R×T FE & controls)	(5) Full Sample	(6) Full Sample (R×T FE & controls)	(7) Full Sample	(8) Full Sample (R×T FE & controls)
log(trade)	0.233**	0.367**	0.236*	0.358*	0.219**	0.299***	0.214**	0.304***
	(0.109)	(0.163)	(0.130)	(0.190)	(0.0950)	(0.106)	(0.0988)	(0.113)
$\Delta\log$(Population)				3.126***		3.153***		3.151***
				(1.165)		(1.155)		(1.153)
IV Transformation	log(IV)	log(IV)	log(IV)	log(IV)	log(IV + 1)	log(IV + 1)	IHS(IV)	IHS(IV)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region × Time Fixed Effects	No	No	Yes	Yes	No	Yes	No	Yes
First-Stage F-statistic	24.50	10.66	24.39	10.82	13.58	24.51	11.23	18.33
Within R^2	0.345	0.444	0.533	0.556	0.470	0.549	0.469	0.550
Number of Observations	622	915	931	888	974	888	974	888
Number of Countries	58	82	86	86	86	86	86	86

Standard errors in parentheses are clustered at the country level.
All first-stage F-statistics satisfy the rule of thumb $F > 10$, thusly I conclude that we are not dealing with issues of weak instruments.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

VI. Conclusion

Following the methodology and model implemented by Caselli and Coleman (2006), I expand their single cross-country analysis of 52 countries in 1988 into a large panel data analysis of 114 countries over the years 1950-2014. I employ a constant elasticity of substitution production function that allows for imperfect substitution across two labor aggregates – skilled and unskilled la- bor. By constructing country-year specific labor series and combining that with across-country and across-time estimates of skilled wage premiums, I confirm their main finding that richer countries are relatively better at using skilled labor and that poorer countries are relatively better at using unskilled labor. Moreover, I broaden and develop their main conclusion by finding that this reality of skill biased technology differences has been a consistent and pervasive feature globally for the second half of the 20th century and into the first decades of the 21st century. These results strongly indicate that the orthodox view that cross-country incomes vary by a single multiplicative TFP does not adequately characterize the technical efficiencies of countries. Moreover, it appears that the orthodox view that all that is required to remedy the observed cross-country income variation is to simply transfer the technology and technical efficiencies of richer countries to poorer countries, is both overly simplistic and not welfare maximizing.

By employing the simple model outlined in Caselli and Coleman (2006) which combines an appropriate choice and a barriers to adoption aspect of technology choice in order to rationalize the calculated technical efficiency choices of countries, I construct annual country-year specific technology frontiers. I find that the evolution of these country-specific and region-specific technology frontiers over time broadly fits with the well-documented observed growth experiences over the second half of the 20th and early 21st centuries – North America and Europe remained at the world technology frontier; significant progress was made in South and East Asia; the Middle East and Latin America display attenuated growth followed by stagnation; Sub-Saharan Africa remains desperately behind. I exploit the nature of the simple model in Caselli and Coleman (2006) to investigate the contribution of barriers to technology adoption to the observed cross-country variation in income. I find that, while decreasing slightly, barriers to technology adoption can explain approximately 48% of the observed variation in cross-country income.

Given the salience of barriers to technology adoption, I investigate the effect of trade on in-creasing a country's available technology space (and thereby decreasing its barriers to technology adoption). I employ an instrumental variable estimation approach, controlling for country and time fixed effects (in addition to other controls), in order to uncover the causal effect of trade on technology space. I rely on the time-varying geography-based trade instrument constructed in Magistretti and Tabellini (2019), who use the heterogeneity arising from the benefits of air route transport vis-à-vis sea route transport to construct an exogenous predicted trade measure. Conclusively, I find that trade has a robust and statistically significant causal effect on a country's technology space, with my estimates indicating that a 10% increase in trade volume gives rise to approximately a 3% increase in a country's available technology space.

VII. Appendix A: Wages and Marginal Products

Recall the production function:

$$y = k^{\alpha}[(A_u L_u)^{\sigma} + (A_s L_s)^{\sigma}]^{\frac{1-\alpha}{\sigma}}$$

Assuming that in equilibrium, factors of production are paid their marginal product, where skilled labor is paid wage w_s and unskilled labor is paid w_u, we can write the ratio of wages as

$$\frac{w_s}{w_u} = \frac{MPL_s}{MPL_u} = \frac{\frac{\partial y}{\partial L_s}}{\frac{\partial y}{\partial L_u}}$$

First, I find the marginal product of unskilled labor, L_u:

$$\begin{aligned}\frac{\partial y}{\partial L_u} &= \frac{\partial}{\partial L_u}\{k^{\alpha}[(A_u L_u)^{\sigma} + (A_s L_s)^{\sigma}]^{\frac{1-\alpha}{\sigma}}\} \\ &= k^{\alpha}\frac{1-\alpha}{\sigma}[(A_u L_u)^{\sigma} + (A_s L_s)^{\sigma}]^{\frac{1-\alpha}{\sigma}-1}\sigma(A_u L_u)^{\sigma-1}A_u \\ \Leftrightarrow \frac{\partial y}{\partial L_u} &= k^{\alpha}(1-\alpha)[(A_u L_u)^{\sigma} + (A_s L_s)^{\sigma}]^{\frac{1-\alpha}{\sigma}-1}(A_u L_u)^{\sigma-1}A_u\end{aligned}$$

Similarly, I find the marginal product of skilled labor, L_s:

$$\begin{aligned}\frac{\partial y}{\partial L_s} &= \frac{\partial}{\partial L_s}\{k^{\alpha}[(A_u L_u)^{\sigma} + (A_s L_s)^{\sigma}]^{\frac{1-\alpha}{\sigma}}\} \\ &= k^{\alpha}\frac{1-\alpha}{\sigma}[(A_u L_u)^{\sigma} + (A_s L_s)^{\sigma}]^{\frac{1-\alpha}{\sigma}-1}\sigma(A_s L_s)^{\sigma-1}A_s \\ \Leftrightarrow \frac{\partial y}{\partial L_s} &= k^{\alpha}(1-\alpha)[(A_u L_u)^{\sigma} + (A_s L_s)^{\sigma}]^{\frac{1-\alpha}{\sigma}-1}(A_s L_s)^{\sigma-1}A_s\end{aligned}$$

I set wages equal marginal products and solve:

$$\begin{aligned}\frac{w_s}{w_u} = \frac{\frac{\partial y}{\partial L_s}}{\frac{\partial y}{\partial L_u}} &= \frac{k^{\alpha}(1-\alpha)[(A_u L_u)^{\sigma}+(A_s L_s)^{\sigma}]^{\frac{1-\alpha}{\sigma}-1}(A_s L_s)^{\sigma-1}A_s}{k^{\alpha}(1-\alpha)[(A_u L_u)^{\sigma}+(A_s L_s)^{\sigma}]^{\frac{1-\alpha}{\sigma}-1}(A_u L_u)^{\sigma-1}A_u} \\ &= \frac{(A_s L_s)^{\sigma-1}A_s}{(A_u L_u)^{\sigma-1}A_u} \\ &= \frac{A_s^{\sigma}L_s^{\sigma-1}}{A_u^{\sigma}L_u^{\sigma-1}} \\ \Leftrightarrow \frac{w_s}{w_u} &= \left(\frac{A_s}{A_u}\right)^{\sigma}\left(\frac{L_s}{L_u}\right)^{\sigma-1}\end{aligned}$$

VIII. Appendix B: Closed-Form Solutions

Recall the production function

$$y = k^{\alpha}[(A_u L_u)^{\sigma} + (A_s L_s)^{\sigma}]^{\frac{1-\alpha}{\sigma}}$$

and the wage-ratio equation

$$\frac{w_s}{w_u} = \left(\frac{A_s}{A_u}\right)^{\sigma}\left(\frac{L_s}{L_u}\right)^{\sigma-1}$$

I will begin by solving for A_u. First, I rearrange the wage-ratio equation.

$$\frac{w_s}{w_u} = \left(\frac{A_s}{A_u}\right)^{\sigma}\left(\frac{L_s}{L_u}\right)^{\sigma-1}$$
$$\frac{w_s}{w_u} = \frac{A_s^{\sigma}}{A_u^{\sigma}}\frac{L_s^{\sigma}}{L_u^{\sigma}}\frac{L_u}{L_s}$$
$$A_u^{\sigma}\frac{w_s}{w_u}\frac{L_s}{L_u} = \frac{A_s^{\sigma}L_s^{\sigma}}{L_u^{\sigma}}$$
$$A_u^{\sigma}\left(\frac{w_s L_s}{w_u L_u}\right) = \left(\frac{A_s L_s}{L_u}\right)^{\sigma}$$

Then, I rearrange the production function.

$$y = k^{\alpha}[(A_u L_u)^{\sigma} + (A_s L_s)^{\sigma}]^{\frac{1-\alpha}{\sigma}}$$
$$(yk^{-\alpha})^{\frac{\sigma}{1-\alpha}} = (A_u L_u)^{\sigma} + (A_s L_s)^{\sigma}$$
$$y^{\frac{\sigma}{1-\alpha}}k^{\frac{-\alpha\sigma}{1-\alpha}} = A_u^{\sigma}L_u^{\sigma} + A_s^{\sigma}L_s^{\sigma}$$
$$\frac{y^{\frac{\sigma}{1-\alpha}}k^{\frac{-\alpha\sigma}{1-\alpha}}}{L_u^{\sigma}} = A_u^{\sigma} + \frac{A_s^{\sigma}L_s^{\sigma}}{L_u^{\sigma}}$$
$$\frac{y^{\frac{\sigma}{1-\alpha}}k^{\frac{-\alpha\sigma}{1-\alpha}}}{L_u^{\sigma}} = A_u^{\sigma} + \left(\frac{A_s L_s}{L_u}\right)^{\sigma}$$

Now, given the two rearranged forms

$$A_u^{\sigma}\left(\frac{w_s L_s}{w_u L_u}\right) = \left(\frac{A_s L_s}{L_u}\right)^{\sigma} \quad \text{and} \quad \frac{y^{\frac{\sigma}{1-\alpha}}k^{\frac{-\alpha\sigma}{1-\alpha}}}{L_u^{\sigma}} = A_u^{\sigma} + \left(\frac{A_s L_s}{L_u}\right)^{\sigma}$$

I substitute the former into the latter and solve for A_u

$$\frac{y^{\frac{\sigma}{1-\alpha}}k^{\frac{-\alpha\sigma}{1-\alpha}}}{L_u^{\sigma}} = A_u^{\sigma} + A_u^{\sigma}\left(\frac{w_s L_s}{w_u L_u}\right)$$
$$\frac{y^{\frac{\sigma}{1-\alpha}}k^{\frac{-\alpha\sigma}{1-\alpha}}}{L_u^{\sigma}} = A_u^{\sigma}\left[1 + \frac{w_s L_s}{w_u L_u}\right]$$
$$\frac{y^{\frac{\sigma}{1-\alpha}}k^{\frac{-\alpha\sigma}{1-\alpha}}}{L_u^{\sigma}} = A_u^{\sigma}\left[\frac{w_u L_u}{w_u L_u} + \frac{w_s L_s}{w_u L_u}\right]$$
$$\frac{y^{\frac{\sigma}{1-\alpha}}k^{\frac{-\alpha\sigma}{1-\alpha}}}{L_u^{\sigma}} = A_u^{\sigma}\left[\frac{w_u L_u + w_s L_s}{w_u L_u}\right]$$

$$\Leftrightarrow A_u = \frac{y^{\frac{1}{1-\alpha}} k^{\frac{-\alpha}{1-\alpha}}}{L_u} \left[\frac{w_u L_u}{w_u L_u + w_s L_s}\right]^{\frac{1}{\sigma}}$$

I solve for A_s in an identical fashion. First, I rearrange the wage-ratio equation.

$$\begin{aligned}
\frac{w_s}{w_u} &= \left(\frac{A_s}{A_u}\right)^{\sigma} \left(\frac{L_s}{L_u}\right)^{\sigma-1} \\
\frac{w_s}{w_u} &= \frac{A_s^{\sigma}}{A_u^{\sigma}} \frac{L_s^{\sigma}}{L_u^{\sigma}} \frac{L_u}{L_s} \\
A_u^{\sigma} \frac{L_u^{\sigma}}{L_s^{\sigma}} \frac{w_s}{w_u} &= A_s^{\sigma} \frac{L_u}{L_s} \\
A_u^{\sigma} \frac{L_u^{\sigma}}{L_s^{\sigma}} &= A_s^{\sigma} \frac{w_u}{w_s} \frac{L_u}{L_s} \\
\left(\frac{A_u L_u}{L_s}\right)^{\sigma} &= A_s^{\sigma} \left(\frac{w_u L_u}{w_s L_s}\right)
\end{aligned}$$

Then, I rearrange the production function in an analogous way.

$$\begin{aligned}
y &= k^{\alpha}\left[(A_u L_u)^{\sigma} + (A_s L_s)^{\sigma}\right]^{\frac{1-\alpha}{\sigma}} \\
(y k^{-\alpha})^{\frac{\sigma}{1-\alpha}} &= (A_u L_u)^{\sigma} + (A_s L_s)^{\sigma} \\
y^{\frac{\sigma}{1-\alpha}} k^{\frac{-\alpha\sigma}{1-\alpha}} &= A_u^{\sigma} L_u^{\sigma} + A_s^{\sigma} L_s^{\sigma} \\
\frac{y^{\frac{\sigma}{1-\alpha}} k^{\frac{-\alpha\sigma}{1-\alpha}}}{L_s^{\sigma}} &= \frac{A_u^{\sigma} L_u^{\sigma}}{L_s^{\sigma}} + A_s^{\sigma} \\
\frac{y^{\frac{\sigma}{1-\alpha}} k^{\frac{-\alpha\sigma}{1-\alpha}}}{L_s^{\sigma}} &= \left(\frac{A_u L_u}{L_s}\right)^{\sigma} + A_s^{\sigma}
\end{aligned}$$

Now, given the two rearranged forms

$$\left(\frac{A_u L_u}{L_s}\right)^{\sigma} = A_s^{\sigma} \left(\frac{w_u L_u}{w_s L_s}\right) \quad \text{and} \quad \frac{y^{\frac{\sigma}{1-\alpha}} k^{\frac{-\alpha\sigma}{1-\alpha}}}{L_s^{\sigma}} = \left(\frac{A_u L_u}{L_s}\right)^{\sigma} + A_s^{\sigma}$$

I substitute the former into the latter and solve for A_s.

$$\begin{aligned}
\frac{y^{\frac{\sigma}{1-\alpha}} k^{\frac{-\alpha\sigma}{1-\alpha}}}{L_s^{\sigma}} &= A_s^{\sigma} \left(\frac{w_u L_u}{w_s L_s}\right) + A_s^{\sigma} \\
\frac{y^{\frac{\sigma}{1-\alpha}} k^{\frac{-\alpha\sigma}{1-\alpha}}}{L_s^{\sigma}} &= \left[\frac{w_u L_u}{w_s L_s} + 1\right] A_s^{\sigma} \\
\frac{y^{\frac{\sigma}{1-\alpha}} k^{\frac{-\alpha\sigma}{1-\alpha}}}{L_s^{\sigma}} &= \left[\frac{w_u L_u}{w_s L_s} + \frac{w_s L_s}{w_s L_s}\right] A_s^{\sigma} \\
\frac{y^{\frac{\sigma}{1-\alpha}} k^{\frac{-\alpha\sigma}{1-\alpha}}}{L_s^{\sigma}} &= \left[\frac{w_u L_u + w_s L_s}{w_s L_s}\right] A_s^{\sigma} \\
\Leftrightarrow A_s &= \frac{y^{\frac{1}{1-\alpha}} k^{\frac{-\alpha}{1-\alpha}}}{L_s} \left[\frac{w_s L_s}{w_u L_u + w_s L_s}\right]^{\frac{1}{\sigma}}
\end{aligned}$$

IX. Appendix C: The Representative Firm's First Order Condition

At optimum:

$$y = F(k, A_u, L_u, A_s, L_s)$$
$$0 = \frac{\partial F}{\partial k}dk + \frac{\partial F}{\partial A_u}dA_u + \frac{\partial F}{\partial L_u}dL_u + \frac{\partial F}{\partial A_s}dA_s + \frac{\partial F}{\partial L_s}dL_s$$
$$\frac{\partial F}{\partial A_u} = -\frac{\partial F}{\partial k}\frac{dk}{dA_u} - \frac{\partial F}{\partial L_u}\frac{dL_u}{dA_u} - \frac{\partial F}{\partial A_s}\frac{dA_s}{dA_u} - \frac{\partial F}{\partial L_s}\frac{dL_s}{dA_u}$$

Given that $\frac{dk}{dA_u} = \frac{dL_u}{dA_u} = \frac{dL_s}{dA_u} = 0$, this reduces to:

$$\frac{\partial F}{\partial A_u} = -\frac{\partial F}{\partial A_s}\frac{dA_s}{dA_u}$$

I solve for the first unknown, $\frac{\partial F}{\partial A_u}$:

$$\frac{\partial F}{\partial A_u} = \frac{\partial}{\partial A_u}\{k^{\alpha}[(A_uL_u)^{\sigma} + (A_sL_s)^{\sigma}]^{\frac{1-\alpha}{\sigma}}\}$$
$$= k^{\alpha}\frac{1-\alpha}{\sigma}[(A_uL_u)^{\sigma} + (A_sL_s)^{\sigma}]^{\frac{1-\alpha}{\sigma}-1}\sigma(A_uL_u)^{\sigma-1}L_u$$
$$\Leftrightarrow \frac{\partial F}{\partial A_u} = k^{\alpha}(1-\alpha)[(A_uL_u)^{\sigma} + (A_sL_s)^{\sigma}]^{\frac{1-\alpha}{\sigma}-1}(A_uL_u)^{\sigma-1}L_u$$

I solve for the second unknown, $\frac{\partial F}{\partial A_s}$:

$$\frac{\partial F}{\partial A_s} = \frac{\partial}{\partial A_s}\{k^{\alpha}[(A_uL_u)^{\sigma} + (A_sL_s)^{\sigma}]^{\frac{1-\alpha}{\sigma}}\}$$
$$= k^{\alpha}\cdot\frac{1-\alpha}{\sigma}[(A_uL_u)^{\sigma} + (A_sL_s)^{\sigma}]^{\frac{1-\alpha}{\sigma}-1}\cdot\sigma(A_sL_s)^{\sigma-1}\cdot L_s$$
$$\Leftrightarrow \frac{\partial F}{\partial A_s} = k^{\alpha}(1-\alpha)[(A_uL_u)^{\sigma} + (A_sL_s)^{\sigma}]^{\frac{1-\alpha}{\sigma}-1}(A_sL_s)^{\sigma-1}L_s$$

I solve for the third unknown, $\frac{dA_s}{dA_u}$:

First, notice that we can rewrite the constraint $(A_s)^{\omega} + \gamma(A_u)^{\omega} \leq B$ as $A_s = [B - \gamma(A_u)^{\omega}]^{\frac{1}{\omega}}$.

Now, differentiate A_s with respect to A_u:

$$\frac{dA_s}{dA_u} = \frac{d}{dA_u}\{[B - \gamma(A_u)^{\omega}]^{\frac{1}{\omega}}\}$$
$$= \frac{1}{\omega}[B - \gamma(A_u)^{\omega}]^{\frac{1}{\omega}-1}\cdot -\gamma\omega(A_u)^{\omega-1}$$
$$\Leftrightarrow \frac{dA_s}{dA_u} = [B - \gamma(A_u)^{\omega}]^{\frac{1-\omega}{\omega}}\cdot -\gamma(A_u)^{\omega-1}$$

Now, notice that $[B - \gamma(A_u)^{\omega}]^{\frac{1-\omega}{\omega}} = (A_s)^{1-\omega}$.

Substituting, we get:

$$\frac{dA_s}{dA_u} = -\gamma(A_u)^{\omega-1}(A_s)^{1-\omega}$$

Therefore,

$$\frac{\partial F}{\partial A_u} = -\frac{\partial F}{\partial A_s}\frac{dA_s}{dA_u}$$

$$\begin{aligned}\left(k^{\alpha}(1-\alpha)\left[(A_uL_u)^{\sigma}+(A_sL_s)^{\sigma}\right]^{\frac{1-\alpha}{\sigma}-1}(A_uL_u)^{\sigma-1}L_u\right) \\ = -\left(k^{\alpha}(1-\alpha)\left[(A_uL_u)^{\sigma}+(A_sL_s)^{\sigma}\right]^{\frac{1-\alpha}{\sigma}-1}(A_sL_s)^{\sigma-1}L_s\right) \\ \times\left(-\gamma(A_u)^{\omega-1}(A_s)^{1-\omega}\right)\end{aligned}$$

$$(A_uL_u)^{\sigma-1}L_u = (A_sL_s)^{\sigma-1}L_s\gamma(A_u)^{\omega-1}(A_s)^{1-\omega}$$

$$A_u^{\sigma-\omega} = \gamma\frac{L_s^{\sigma}}{L_u^{\sigma}}A_s^{\sigma-\omega}$$

$$\left(\frac{A_s}{A_u}\right)^{\omega-\sigma} = \gamma\left(\frac{L_s}{L_u}\right)^{\sigma}$$

X. Appendix D: Graphs for Parameter Robustness

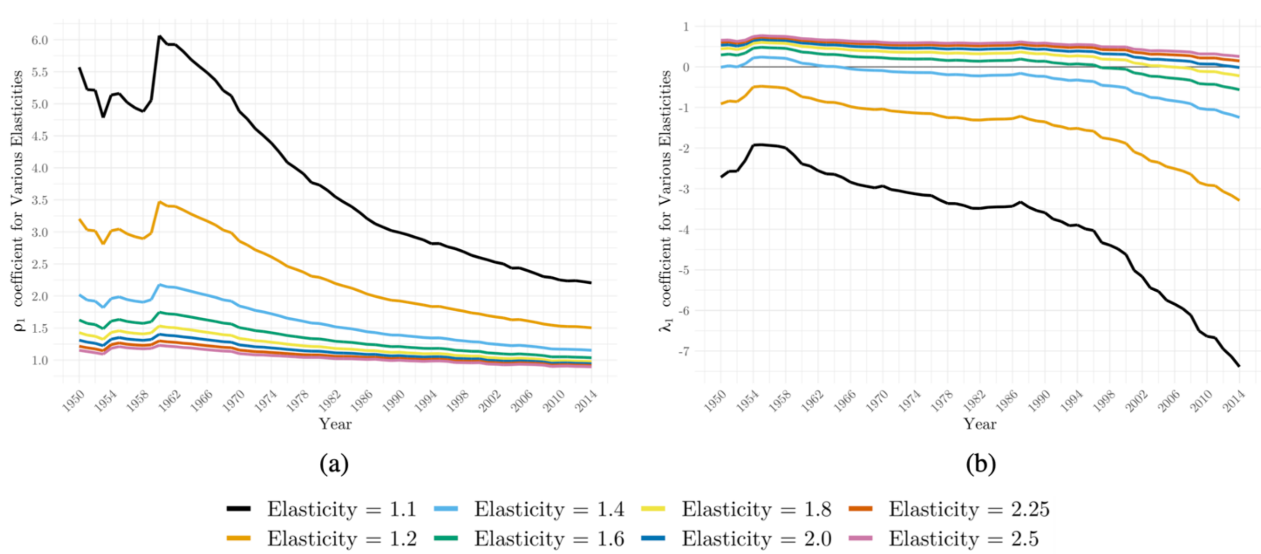
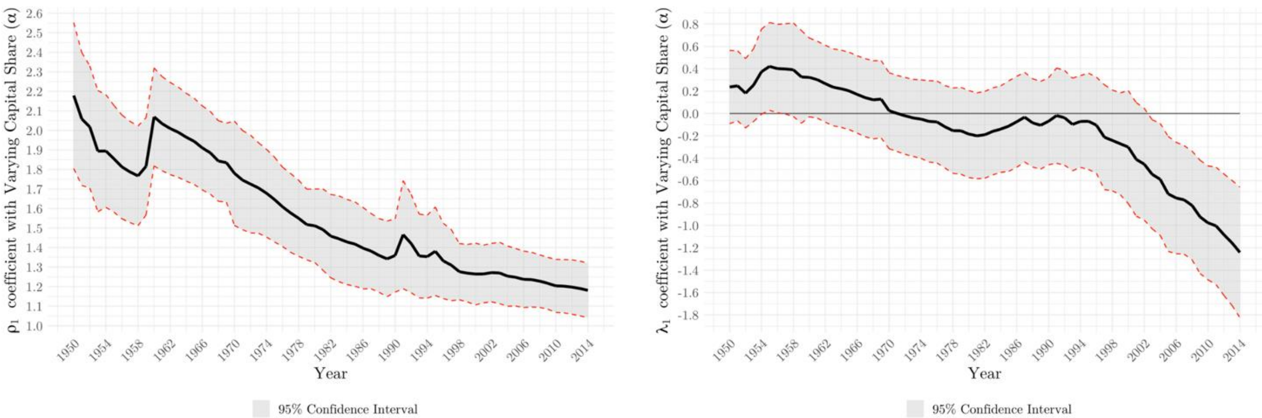


Figure 18: Robustness of Elasticity of Substitution

Figure 18 presents the results of solving for A_u and A_s (equations (4) and (5) respectively) and then regressing equation (8) to obtain ρ_1 estimates presented in Figure 18(a) and regressing equation (9) to obtain λ_1 estimates presented in Figure 18(b), for a host of plausible values of the elasticity of substitution. Recall that if $\rho_1 > \lambda_1 \geq 0$ we have the case of *relative* skill bias, and if $\rho_1 > 0$ while $\lambda_1 < 0$ we have the case of *absolute* skill bias. As the elasticity of substitution tends toward 1, skilled and unskilled labor become more imperfect substitutes, and we see more evidence of an *absolute* skill bias. As the elasticity of substitution tends toward 2.5, skilled and unskilled labor become more perfect substitutes, and we see more evidence of a *relative* skill bias.



(a) (b)

Figure 19: Robustness with Varying Capital Share of Income

Figure 19 presents the results of solving for A_u and A_s (equations (4) and (5) respectively) and then regressing equation (8) to obtain ρ_1 estimates presented in Figure 19(a) and regressing equation (9) to obtain λ_1 estimates presented in Figure 19(b), where instead of assuming that the capital share of income $\alpha = 1/3$, I use data on the labor share of income from the Penn World Table to get country-year specific values according to the equation $\alpha_{i,t} = 1 -$ Labor Share of Income$_{i,t}$. As is evident in Figure 19, we see strong evidence of relative skill bias until the early 2000's, at which point we begin to see strong evidence of an absolute skill bias.

<u>Appendix E:</u> Proof of Solution to the Constrained Maximization Problem

Claim: *For each country in each year, a solution to the following constrained maximization problem exists and is unique.*

Proof. Let $f(A_u, A_s)$ be the continuous objective function and let $h(A_u, A_s)$ be the continuous constraint. Let $A_u \in \mathcal{A}_u$, where $\mathcal{A}_u$ is the set of possible unskilled labor technologies. As implied by the constraints, $\mathcal{A}_u = \left[0, \left(\frac{B^\star}{\gamma^\star}\right)^{\frac{1}{\omega^\star}}\right] \subseteq \mathbb{R}$. Being a closed and bounded subset of the real line, $\mathcal{A}_u$ is a compact set in $(\mathbb{R}, d_2)$. Let $A_s \in \mathcal{A}_s$, where $\mathcal{A}_s$ is the set of possible skilled labor technologies. As implied by the constraints, $\mathcal{A}_s = \left[0, (B^\star)^{\frac{1}{\omega^\star}}\right] \subseteq \mathbb{R}$. Being a closed and bounded subset of the real line, $\mathcal{A}_s$ is a compact set in $(\mathbb{R}, d_2)$. $\mathcal{A}_u \times \mathcal{A}_s \subseteq \mathbb{R}^2$ being a closed and bounded subset of $\mathbb{R}^2$ is therefore a compact set in $(\mathbb{R}^2, d_2)$. The feasible constraint set of technology choices is

$$\mathcal{T} = \{(A_u, A_s): A_u, A_s \in \mathcal{A}_u \times \mathcal{A}_s \ \ and \ \ h(A_u, A_s) \leq B^\star\}$$

$\mathcal{T}$ is a closed set because it is the pre-image of a closed set under a continuous function – that is $h^{-1}([0, B^\star])$.
$\mathcal{T}$ is compact because it is a closed subset of the compact set $\mathcal{A}_u \times \mathcal{A}_s$.

Lemma. $\mathcal{T}$ is non-empty.

Proof. The choice set where there is no technology, that is $(A_u, A_s) = (0,0)$ so that $h(A_u, A_s) \leq 0$, lies in the set $\mathcal{T}$. Therefore $\mathcal{T} \neq \emptyset$.

Given that f is a continuous function on the nonempty compact set $\mathcal{T}$, by the Extreme Value Theorem, f has a maximum at some point over $\mathcal{T}$.

Given that $\mathcal{T} \subseteq \mathbb{R}^2$ and that f is strictly concave, then f has at most one maximizer.

Conclusion: Therefore, the solution to the constrained maximization problem exists and is unique. ■

XI. References

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