Heckscher-Ohlin and the global increase of skill premia: factor intensity reversals to the rescue*

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Abstract

This paper advances the claim that trade liberalization has been a strong force behind the global increase of skill premia, in particular in skill-scarce, developing countries. By introducing skill-intensity reversals, the Heckscher-Ohlin framework captures the stylized facts of the global increase in skill premia, both in developed and in less-developed countries. I support the model by evidence on industrial structure and changes in relative prices. The calibrated model is also successful quantitatively: small changes in relative goods' prices are consistent with much larger increases in skill premia that have been observed in the data. This suggests that tariff reductions might have been a strong driving force behind the increase in global inequality and weakens the conclusion that other forces have been dominant. The analysis also suggests an explanation for protection of skill-unintensive sectors both in developed- and less-developed countries.

Keywords: Heckscher-Ohlin, Factor intensity reversals, Skill premium, Elasticity of substitution, Trade liberalization.
JEL Classification: F11, F16

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1 Introduction

One of the most prevalent economic phenomena in the last two decades of the 20th century has been the increase in skill premia in many countries around the globe—skilled workers have been receiving a higher share of income and higher wages relative to their less-skilled fellow workers. The magnitude of this increase varies considerably across countries, but is economically large almost everywhere. To put this in context, Acemoglu (2003) reports a rise in the college premium in the US of 36 percent points (1979 to 1996), Behrman et al. (2003) report that the average university/primary education premium in 18 Latin American countries increased by 60 percent points (1990 to 1998), and Gorg and Strobl (2002) report a rise in the white-collar/blue-collar premium in Ghana of 207 percent points in (1991 to 1997). As Hoekman and Winters (2005) put it, this phenomenon has indeed been global, as both developed and less-developed countries have experienced it.

This paper advances the claim that liberalization in final goods' trade might have been a strong force behind the increases in skill premia. In order to make this point, I present a simple general equilibrium model of international trade, based on the Heckscher-Ohlin-Samuelson (HOS) framework, that captures the stylized facts of global increases in skill premia. The standard HOS model has not been successful in explaining the rise in skill premia in relatively skill-scarce economies, despite its reasonable predictions for skill-abundant ones; while the model predicts a decrease in skill premia in skill-scarce, less-developed countries, the opposite has been observed. The assumption that delivers this counterfactual result is the "no factor intensity reversals" assumption.

The model presented here incorporates factor intensity reversals in skill (henceforth, *skill*-intensity reversals), which allow the skill premium to rise simultaneously in the skill-abundant "North" and in the skill-scarce "South". Thus the model does not exhibit the counterfactual prediction that trade liberalization lowers skill premia in less-developed countries—and it becomes consistent with observations on skill premia, both in skill-abundant developed and skill-scarce less-developed countries, both qualitatively and, to some degree, quantitatively.

Skill-intensity reversals are possible whenever elasticities of substitution between factors are not equal in all sectors. Whether this is true or not is an empirical question—to which the answer is yes. One can simply take it at face value that some goods may be produced with more flexible technologies, but some economics can be suggested as well. Industries that have existed for some time may exhibit very low elasticities of substitution because the technology has evolved to the point at which the "right" mix of skills has been identified. An example of this kind of industry is textiles and apparel. Other industries that are younger or that are rapidly evolving may exhibit higher elasticities of substitution because the "best" mix of skills is not yet known or because technological progress has revealed a wider mix of skill mixes that are equally productive (i.e., they all lie on the same iso-revenue curve). An example of this kind of industry is capital goods or machinery and transportation equipment. If both types of industry exist in two countries, then their respective factor abundance (if sufficiently different) may dictate different skill intensities in the same industry and, hence, different factor price equilibria and skill premia.

Therefore, in order to substantiate the model, I estimate its key parameters, namely elasticities of substitution between skilled-labor and unskilled-labor, in the US, Chile and Brazil using manufacturing survey data. The estimates of elasticities of substitution (EoS) between skilled and unskilled labor exhibit considerable variation across manufacturing industries, and their pattern may give rise to skill-intensity reversals. I then use these estimates to "calibrate" the model and then simulate the effects of trade barrier elimination and tariff reductions on skill premia. The model's predictions are consistent with observed patterns of skill premia and their changes—both for the "North" and the "South".

One conclusion that follows from the simulation is that very small changes in relative prices can wield very large changes on relative wages. This is nothing but a manifestation of the Stolper-Samuelson Theorem, but the actual magnitudes are telling. Therefore, studies that claim that changes in relative prices were not *sufficiently* large to explain the increases in the skill premium may be underestimating their effect on the skill premium[1]. Thus, the "tail" (relative prices) may have "wagged the dog" (relative wages).

However, for this story to be plausible to any degree, relative prices need to move in the "right" direction for the skill premium to rise both in the North and South. Using the benchmark prices for disaggregated goods from the Penn World Tables PPP estimates, I examine changes in relative prices in many countries and find some evidence that relative prices have changed in the direction that supports the predictions of the model, although the evidence is not clear-cut.

Following the conclusion of the Tokyo GATT round in 1979, subscribing countries lowered their tariff and non-tariff barriers considerably. Heckscher-Ohlin trade theory relates goods' prices to wages (or, more generally, factor prices). The timing of the implementation of the aforementioned trade barrier reductions in many countries coincides with increases in their wage inequality, sometimes reversing previous trends[2]. Thus, it is only natural to suspect that tariff reductions caused the increases in skill premia.

According to Heckscher-Ohlin trade theory, skill-abundant (developed) countries

[1] For example, Sachs and Shatz (1994) find that from 1978 to 1989 the relative price of skill-intensive manufactured goods in the US increased by 9%. This change may have been more than enough to trigger rises in skill premia that have been observed in the US during this preiod.

[2] E.g., in Mexico after the 1985 reforms. See Hanson and Harrison (1999).

have a comparative advantage in exporting skill-intensive goods, whereas skill-scarce (less-developed) countries have a comparative advantage in exporting skill-*un*intensive goods. Thus, falling trade barriers would induce an increase in the skill premium in developed countries, and a *fall* in the skill premium in less-developed countries—which is at strong odds with the evidence. This has led economists to seek other mechanisms that might explain the global rise in skill premia.

Based on empirical analysis, Berman, Bound and Griliches (1994) and Katz and Autor (1999) have concluded that skill-biased technological change (SBTC) has been the main source for the increase in wage inequality in the US. More recently, Acemoglu (2003) has provided a theoretical framework that endogenizes such biased technical change; he also shows how increased openness might strengthen this mechanism and propagate its effects to less-developed countries. However, Katz and Murphy (1992) find that SBTC is a slow and gradual process, whereas the timing of the sharp increases in wage inequality coincides with trade liberalization in the US. Nevertheless, Autor, Katz and Krueger (1998) conclude that the demand for skills must have increased after 1970.

Feenstra and Hanson (1996a) suggest that outsourcing of intermediate inputs is a different mechanism by which increased openness has increased wage inequality both in developed and less-developed countries. If developed countries transfer the production of their least skill-intensive activities to less-developed countries where these activities are relatively skill intensive, the result is an increase in skill intensity and skill premia in both country types. Feenstra and Hanson (1997) test their predictions on Mexican data and conclude that this effect is indeed economically important.

Wood (1995, 1997) claims that the pronounced increase of importation of low skill-intensity goods in developed countries has expanded the effective supply of unskilled labor there. Thus, the factor content of those imports is the mechanism by which trade has caused the increase in wage inequality in developed countries. This might also explain the increase in the skill premia of middle-income, Latin-American countries; following the entry of China, India and other South-Asian countries into the world trading activity in the 1980s, Latin-American countries became relatively skill-abundant, and might have resembled developed countries than skill-scarce China and India (at the time). Nevertheless, this does not offer an explanation for the increase in skill premia in the least-developed countries.

Other economists have tried to reconcile the counterfactual predictions of the HOS model with the facts by suggesting that other forces have increased skill premia in less-developed countries. For instance, Milanovic and Squire (2005) claim that the decline in the power of unions has been such a force. If unionization is higher in sectors that had higher tariff protection or unionization is more prevalent among unskilled workers, and if trade liberalization is coupled with labor market reforms[3], then the net effect

[3]Milanovic and Squire claim that trade liberalization usually comes within a package of other

could be the opposite of what the HOS model alone suggests. Milanovic and Squire conclude that since skill premia have indeed increased in less-developed countries, it must be the case that unionization has fallen there by enough to overturn what is suggested by the HOS model.

Yet another interesting mechanism has been suggested by Krugman (2000). If education is only a signal for innate ability, which is private information, then small changes in relative prices might induce a regime-switch from a pooling equilibrium to a separating one. In the separating equilibrium more high-ability types have an incentive to reveal their type, thus seeking more formal education (a proxy for "skill") and thus increasing the skill premium.

This paper builds on the work of Minhas (1962), who considered capital-labor intensity reversals in the HOS model. Here I apply his analysis to *skill*-intensity reversals and extend it. By relaxing the stringent assumption of "no factor intensity reversals" the model's predictions for trade opening become consistent with the stylized facts of skill premia.

The analysis also provides a potential explanation for why less-developed countries protected their skill-*un*intensive sectors, which have a comparative advantage under standard assumptions and would not require protection. With skill-intensity reversals, these sectors might be in direct international competition with skill-intensive sectors in developed countries, if they are producing the same goods (with different skill intensity). If the skill-intensive sector in the North is sufficiently more productive in producing these goods, then the unskilled labor the South might demand protection of the skill-unintensive sector there.

The modified model succeeds where the standard one fails due to the fact that it allows two cones of diversification with only *two* goods. The North produces in one and the South in the other. Each country produces *both goods* with different input mixes and exhibits different skill premia, although technology is the same in both countries.

Most related to this last point is the conclusion of Schott (2003). After constructing "Heckscher-Ohlin aggregates" that correspond to conceptual *capital*-intensive and *capital*-unintensive goods, Schott finds that all countries in his sample can be located within two cones of diversification. However, Schott's cone structure requires *three* goods, so each country does not produce one of the goods and must import all of its consumption of that good. Moreover, Schott considers capital and non-differentiated labor as factors of production. In this sense his work is orthogonal to this paper: here both goods are produced by both countries, and I consider skilled and unskilled labor as factors of production.

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reforms, one of which is labor market reform, which diminishes union power. Olson (1982, chapter 5) describes how trade liberalization alone could diminish the power of unions, without an explicit labor market reform. The case of the car-industry workers union IG Metal in Germany after enlargement of the EU in May 2004 provides a recent compelling exmaple.

Factor intensity reversals are possible whenever elasticities of substitution between factors are not equal in all sectors. A weak version of the "no FIRs" assumption is that the variation in skill premia across countries is empirically too small to allow FIR in practice[4]. It is argued here that this is the exception, rather than the rule, i.e. that elasticities of substitution are not equal across sectors and that the variation of skill premia across countries is indeed large enough to make possibility a practice. The next section provides evidence to support this last claim. Section 3 outlines the model, which is supported by evidence in Section 4. In Section 5 I present evidence on changes in relative prices. In Section 6 I discuss the "calibration" of the model and simulate comparative statics. Section 7 concludes.

2 Skill premia: three stylized facts

The increases of skill premia across the globe are widely documented and their magnitudes are strikingly large. For example, in the United States, the relative wage of college graduates to high school graduates increased by roughly 24% from 1979 to 1996[5]. A similar magnitude of change has been observed in the United Kingdom. In other OECD countries such large changes have not been observed; see Katz and Autor (1999)[6]. In European countries this is probably due to the "rigid" wage structure; since wages could not adjust, the flip-side was a dramatic increase in unemployment among low-skill workers (Freeman (1995)).

Table 1 gives a taste of how widespread the rise in skill premia is and a sense of the magnitudes involved[7]. The years are selected according to the studies mentioned in the sources for the table; they correspond to periods of increased openness to trade[8].

[4]In light of Minhas' work, Leontief (1964) examined empirically the variation in wages relative to returns to capital (w/r) across countries and sectors and concluded that they are seldom large enough to be consistent with capital-labor intensity reversals in practice, although he did find that they are large enough in some sectors across countries.

[5]This has been widely documented and analyzed, e.g. by Katz and Murphy (1992), Berman, Bound and Griliches (1994) and Katz and Autor (1999). Most of the increase in the skill premia in the U.S. has been caused by plummeting high school graduates' real wages in the face of a modest increase in college graduates' real wages.

[6]Katz and Autor (1999) document changes in 90:10 log ratios of male earnings. Small increases have been observed in Australia, Canada and Japan; and moderate increases in Italy and New Zealand. They do not find significant increases for other OECD countries. See their table 10.

[7]In the appendix I reproduce Table 10 from Katz and Autor (1999). The numbers in that table are logs of 90:10 wage ratios, and therefore the levels are not comparable to my Table 1 (e.g., a log ratio of 1 means that the ratio is equal to $e \approx 2.7183$). However, the last column in Katz and Autor's Table 10 is comparable, because it represents percent changes.

[8]In Ghana there was an increase in public-sector real wages in 1992 (following the 1992 elections and increased international aid) which might have contributed to the increase in the skill premium there. However, the data in Gorg and Strobl (2002) are from the manufacturing sector. Moreover,

More evidence on increases in wage premia in some South American countries and cities[9] due to changes in trade regimes is summarized by Wood (1997), who cites various studies carried out by Donald Robbins and coauthors (see references therein). Richardson (1995) cites other studies that corroborate Wood and document similar trends in the same and other developing countries[10] (see references therein). So one can safely conclude that during periods of increased openness skill premia have indeed risen in many countries around the globe[11].

Table 1 also shows that in this small sample the increases in skill premia were much larger in less developed countries (Colombia is atypical in the percent change, although the sample is half the length of the US data). This fact has mostly gone unnoticed in the literature. An exception to this are Milanovic and Squire (2005); they find that occupational Gini coefficients (indicators of skill premia) increased more in poorer countries.

Another important feature of the data—which can also be seen in Table 1[12]—is that the levels of skill premia in developing countries are typically much higher than what is observed in developed countries. Figure 1 shows that skill premia are higher in less developed countries and Figure 2 shows that skill premia are higher in countries that are less skill abundant. The figures use skill premia from 34 developing and less-developed countries around the world, estimated from national surveys during the 1990s by Fernandez et al. (2004). The upshot of using their data is that all skill premia are calculated using the same methodology and based on data that are similar in their wide scope. PPP GDP is taken from the World Bank's World Development Indicators online and average schooling is from Barro and Lee (2000). Table 2 reports all the data[13]. The bivariate regressions that correspond to the relationships in figures yield $R^2 = 0.41$ and 0.47, respectively. Milanovic and Squire (2005) find that occupational Gini coefficients are negatively correlated with income per capita. Repetto and Ventura (1997) find a

most of the increase ocurred in 1993-4 and 1995-6.

[9] Argentina (Buenos Aires), Chile (Santiago), Colombia (seven cities), Costa Rica and Uruguay (Montevideo).

[10] Brazil, Korea, Singapore and Morocco.

[11] In a cross section of 79 countries Milanovic and Squire (2005) find, as they put it, weak evidence that increases in wage inequality are associated with lower tariffs.

[12] China is atypical. Anectdotal evidence indicates that inequality has continued to increase in recent years. Robbins (1996, Figure 4) provides more examples of high levels of skill premia in developing countries: average skill premia are (samples do not coincide) for Chile: 6, Colombia: 4.5, Costa Rica: 3.5, Malaysia: 7, Taiwan: 1.7 and Uruguay: 2.3. ##### WHEN????? #####

[13] The survey years in Fernandez et al. (2004) are not consistent across countries, but all were taken between 1990 and 1998. PPP GDP in constant dollars data is in the same year as the survey for each country; average schooling data is taken from either 1990 or 1995, whichever was closest to the survey year. The skill premium estimate of Paraguay is from 1998, but I prefer to present education data from 1995 rather than 2000, because the latter is a projection. The average schooling estimate in 1995 is 5.73 and the projected estimate for 2000 is 5.74, so this does not affect Figure 2 at all.

negative correlation between skill premia and skill abundance across countries.

We can summarize the stylized facts on skill premia as follows:

1. skill premia are higher in the skill-scarce, less-developed countries, relative to skill-abundant, developed countries;

2. skill premia rose in both country types; and

3. skill premia rose more in the less-developed countries.

The model presented below captures all of these three stylized facts.

3 Skill premia and skill-intensity reversals

The Heckscher-Ohlin model is well known and studied[14]. Therefore I focus only on features which are different from the standard version, and on the main theoretical predictions for trade liberalization. The analysis builds on Minhas (1962).

3.1 A 2x2x2 model

The model consists of two countries, "North" and "South", each of which is populated with a fixed number of workers that are not mobile across countries. All workers have identical homothetic preferences. The workers are either skilled (S) or unskilled (L) and cannot leave their country, but are mobile between sectors[15].

Each country has access to two constant returns to scale technologies that produce two tradable goods (sectors). These technologies are the same across countries up to a neutral productivity shifter, and both use skilled and unskilled labor as factors of production. For a particular sector, output is given by $Q_{ic} = A_{ic}F_i(S_{ic}, L_{ic})$, where $i \in \{1, 2\}$ denotes sectors, $c \in \{n, s\}$ denotes countries and A_{ic} denotes the neutral productivity shifter. I assume that these technologies are of the constant elasticity of substitution (CES) class

$$Q_{ic} = A_{ic}\left[\alpha_i S_{ic}^{\theta_i} + (1-\alpha_i)L_{ic}^{\theta_i}\right]^{1/\theta_i},$$

where α_i is a distribution parameter and $\theta_i \in (-\infty, 1]$ is a substitution parameter[16]. The elasticity of substitution (EoS) between skilled and unskilled labor is $\epsilon_i = 1/(1-\theta_i)$. Notice that the latter three parameters are sector-specific, but are identical across countries.

[14] For an exposition, see Feenstra (2004).

[15] Skilled-labor mobility from less-developed countries to developed ones ("brain drain") only makes the less-developed countries less skill abundant and does not change the results of the following analysis.

[16] One can think of the productivity shifter as capturing capital as well as TFP. If $Q = (T \cdot K^{\gamma})\left[\alpha S^{\theta} + (1-\alpha)L^{\theta}\right]^{\frac{1-\gamma}{\theta}}$, where T and K denote TFP and capital, respectively, then $A = (T \cdot K^{\gamma})$ and all the results derived below hold exactly.

All markets are competitive (i.e. firms and workers are price takers). Since workers are mobile across sectors, the returns to each worker type must be equal in both sectors in equilibrium. Firms maximize profits; by the zero profit condition for CRS technology in a competitive economy, payments to factors exhaust revenues and factor returns are given by the value of their respective marginal products. Let z and w denote the returns to skilled and unskilled labor, respectively. By manipulating the first order conditions for the firms one can express the optimal skill intensity as a function of the skill premium as follows

$$x_{ic} = \left(\frac{\alpha_i}{1-\alpha_i}\right)^{\epsilon_i} \pi_c^{-\epsilon_i},$$

where $x_{ic} = S_{ic}/L_{ic}$ is the skill intensity in sector i in country c, and $\pi_c = z_c/w_c$ is the skill premium in country c. The relative skill intensity across sectors is given by

$$\frac{x_{1c}}{x_{2c}} = \left(\frac{\alpha_1}{1-\alpha_1}\right)^{\epsilon_1} \left(\frac{\alpha_2}{1-\alpha_2}\right)^{-\epsilon_2} \pi_c^{\epsilon_2-\epsilon_1}.$$

It can be seen from this expression that unless $\epsilon_1 = \epsilon_2$, then relative skill intensity between two sectors in a country cannot be determined separately from the level of the skill premium. Moreover, the relationship between the two is not monotone. Without loss of generality, let

$$\epsilon_1 > \epsilon_2.$$

Under this assumption sector 1 is skill intensive relative to sector 2 for low skill premia and the opposite for high values of skill premia.

The standard assumption that allows us to neatly separate the solution for prices from quantities (and then calculate quantities as residuals) is known as "no factor intensity reversals". Under this assumption, for every pair of factor returns (or skill premium) one good will be produced with higher skill intensity relative to the other. As long as both goods are produced[17], the "no FIRs" assumption gives rise to "factor price insensitivity": factor prices are uniquely given only by goods prices—not by factor endowments. In terms of this model, this amounts to assuming $\epsilon_1 = \epsilon_2$.

However, if $\epsilon_1 > \epsilon_2$, this unique relationship does not hold. To illustrate this point I use a Lerner diagram. As can be seen in Figure 3, where $\epsilon_2 = 0$ for expositional purposes (Leontief production function), there are two possible equilibria, which are characterized by two skill premia. The selection between equilibria for a particular country will be determined by its skill abundance. I assume that North is sufficiently skill abundant to be in the top equilibrium and South is sufficiently skill scarce to be in the bottom one. This would also cause the skill premium to be lower in the North.

[17] I.e., factor endowment vectors are within cones of diversification.

Notice that in the North good 1 is produced with greater skill-intensity relative to good 2, whereas the opposite is true in the South. Thus, the general notion of a skill-intensive good becomes a local concept and I adopt the term "locally skill-intensive" to describe exactly that. Notice also that the North produces all goods with higher skill intensity than the South (except when $\epsilon_2 = 0$, in which case good 2 is produced with the same skill-intensity).

The relationship between skill premia and relative prices in a particular country can be written as follows

$$p = \frac{1}{A} \cdot \frac{\left[\alpha_1^{\epsilon_1} \pi^{1-\epsilon_1} + (1-\alpha_1)^{\epsilon_1}\right]^{\frac{1}{1-\epsilon_1}}}{\left[\alpha_2^{\epsilon_2} \pi^{1-\epsilon_2} + (1-\alpha_2)^{\epsilon_2}\right]^{\frac{1}{1-\epsilon_2}}},$$

where $p = p_1/p_2$ and $A = A_1/A_2$. The relationship between the logs of p and π has an inverted U-shape. The derivative of log price with respect to log skill premium is

$$\frac{d \log p}{d \log \pi} = \frac{a_1 \pi^{1-\epsilon_1} - a_2 \pi^{1-\epsilon_2}}{(1 + a_1 \pi^{1-\epsilon_1})(1 + a_2 \pi^{1-\epsilon_2})} \tag{1}$$

$$\begin{cases} > 0 \text{ when } \pi < \pi^* \\ < 0 \text{ when } \pi > \pi^*, \end{cases} \tag{2}$$

where $\pi^* = (a_1/a_2)^{\frac{1}{\epsilon_1 - \epsilon_2}}$ and $a_i = [\alpha_i/(1-\alpha_i)]^{\epsilon_i}$. Since the price-skill premium relationship is monotone outside of π^*'s neighborhood, one can piecewise-invert the function in the two ranges given in (2) without including the unique $p(\pi^*)$ (and all values above it) in the domain and without the critical point π^* in the range. In this case the derivative of the log skill premium with respect to log price is the reciprocal of (1), so one can write

$$\frac{d \log \pi}{d \log p} \begin{cases} > 0 \text{ when } \pi < \pi^* \\ < 0 \text{ when } \pi > \pi^* \end{cases}. \tag{3}$$

The non-monotone price-skill premium relationship will play a key role in explaining rising skill premia both in the North and in the South.

The factor market clearing condition for a particular country is

$$\lambda x_1 + (1-\lambda) x_2 = \overline{x}, \quad \lambda \in (0,1),$$

where $\overline{x} = \overline{S}/\overline{L}$ is the skill abundance in that country and $\lambda = L_1/\overline{L}$. Restricting $\lambda \in (0,1)$ means that both goods are produced; this is equivalent to requiring $x_1 < \overline{x} < x_2$ or $x_2 < \overline{x} < x_1$. Using the market clearing condition one can write the relative labor allocation in equilibrium as a function of the skill premium as follows

$$l(\pi) = \frac{L_1}{L_2} = \frac{\overline{x} - a_2 \pi^{1-\epsilon_2}}{a_1 \pi^{1-\epsilon_1} - \overline{x}}.$$

The relative supply of good 1 in a particular country, $q = Q_1/Q_2$, can also be written as a function of the skill premium as follows

$$q = k \cdot l(\pi) \frac{\left[a_1 \pi^{1-\epsilon_1} + 1\right]^{1/\theta_1}}{\left[a_2 \pi^{1-\epsilon_2} + 1\right]^{1/\theta_2}},$$

where $k = A(1-\alpha_1)^{1/\theta_1}/(1-\alpha_2)^{1/\theta_2}$ is a constant. As with the price-skill premium relationship, this one is also not monotone

$$\frac{d\log q}{d\log \pi} = (1+\overline{x}\pi)\left[\frac{\epsilon_1 x_1}{(x_1-\overline{x})(1+x_1\pi)} + \frac{\epsilon_2 x_2}{(\overline{x}-x_2)(1+x_2\pi)}\right] \tag{4}$$

$$\begin{cases} > 0 & \text{when} \quad x_2 < \overline{x} < x_1 \\ < 0 & \text{when} \quad x_1 < \overline{x} < x_2 \end{cases}. \tag{5}$$

Noting that x_i are functions of the skill premium, it is not surprising that the sign of (4) given by (5) is equivalent to condition (2), i.e.

$$\begin{aligned} x_2 &< \overline{x} < x_1 \iff \pi < \pi^* \\ x_1 &< \overline{x} < x_2 \iff \pi > \pi^*. \end{aligned}$$

However, condition (5) is more informative for understanding comparative statics in light of Figure 4; it tells us, ceteris paribus, how the skill premium and quantities produced respond to price changes conditional on which equilibrium we are in (North or South). For example, if we are in the South, a *decrease* in the relative price of good 1—the skill-*un*intensive good for the South—causes the skill premium to increase there; in the North, an *increase* in the relative price of good 1—the skill-intensive good there—causes the skill premium to rise there. Thus, opposite changes in relative prices in South and North may trigger the same change in the skill premium.

3.2 Trade liberalization

Suppose that both countries are initially in autarky. In general, the equilibrium price and allocation values will be determined by every parameter of the model, but since preferences are restricted to be identical and homothetic, I consider only technology parameters and endowments. The South is characterized by much lower skill abundance than in the North. It is assumed that it is low enough to ensure that the South will be in an equilibrium in which $x_{1s} < \overline{x}_s < x_{2s}$, and a relatively high skill premium $\pi_s > \pi^*$. The North is assumed to be skill abundant enough to be in an equilibrium in which $x_{2n} < \overline{x}_n < x_{1n}$, and a relatively lower skill premium $\pi_n < \pi^*$.

Let good 2 be numeraire and the relative price of good 1 in the North and South be p_n^{aut} and p_s^{aut}, respectively. The relative magnitudes of p_n^{aut} and p_s^{aut}, will be determined by relative skill abundance in both countries, relative productivity of sectors in each country and by all other technological parameters in the production function. Given that I am interested in a situation in which the north exports good 1 to the South, I assume $p_n^{aut} < p_s^{aut}$.[18]

Now suppose that these countries engage in free trade. In this case $p_n^{trade} = p_s^{trade} = p^*$, where the "world" equilibrium price, p^*, will fall between the autarky prices, i.e. $p_n^{aut} < p^* < p_s^{aut}$. This implies that the relative price in the North increases, whereas in the South it falls. Noting the pattern of endowments and the footwork summarized in (3), we have the skill premium increasing in both countries. From (4)-(5) the relative supply of good 1 expands in the North, and it will export the excess supply to the South and import good 2. The opposite will hold in the South. The change of regime from autarky to free trade is purely heuristic and I consider tariff reduction as well; the results remain qualitatively the same.

This analysis also provides a potential explanation to why less-developed countries protect their skill-*un*intensive sectors. In the standard HOS model, the South has a comparative advantage in skill-*un*intensive production and, therefore, would not have to protect that sector from international competition. But with skill-intensity reversals, sector 1 in the South is in direct competition with sector 1 in the North and its workers might like to be protected.

Thus, so far, it has been shown that the model captures two of the stylized facts: that the skill premium is larger in the South; and that following trade liberalization skill premia increase both in the North and in the South. It remains to be shown that the model also captures the third stylized fact, that skill premia increase more in the South. This will be addressed by calibration and comparative statics. More importantly, the postulated structure of the model needs to be supported by some evidence. This is addressed in the next section.

4 Estimating elasticities of substitution

Up to now I have painted a pretty picture. In the following sub-sections I will try to convince that this picture is also a plausible one. In order to do so, I will try to demonstrate that elasticities of substitution between skilled-labor and unskilled-labor are not equal and that they follow the postulated pattern. I.e., the skill-intensive industries in the North exhibit higher elasticities of substitution and the opposite in the South; those industries that are skill-intensive in the North are relatively skill-unintensive in the South.

[18] It can be shown that p_n^{aut} decreases in the skill abundance of the North, and p_s^{aut} increases in the skill abundance of the South. Given the assumptions on the relative skill abundance of each country, $p_n^{aut} < p_s^{aut}$ is a plausible outcome.

In the model there was no capital, but clearly capital plays an important role in reality. However, as long as the elasticity of substitution between capital and each type of labor is equal, it is inconsequential for the results derived above.

Consider the following production function for a particular firm,

$$Q_t = \left\{ \delta K_t^{\gamma} + (1-\delta)\left[\alpha (A_S(t) S_t)^{\theta} + (1-\alpha)(A_L(t) L_t)^{\theta}\right]^{\gamma/\theta} \right\}^{1/\gamma}, \tag{6}$$

where $A_f(t)$ is a factor-augmenting technology index for factor $f \in \{S, L\}$ at time t, and I omit capital's technology index for simplicity. This postulates a CES production function with capital and a labor composite [in square brackets] as factors, and allows for biased technological change. If factor-augmenting technical progress is exponential, then taking logs of the first order conditions for a maximizing firm with respect to skilled-labor and unskilled-labor and rearranging yields

$$\begin{aligned} \ln x_t &= \kappa - \epsilon \ln \pi_t + (\epsilon - 1)(g_S - g_L) \cdot t \\ &= \kappa - \epsilon \ln \pi_t + \lambda \cdot t, \end{aligned} \tag{7}$$

where $\lambda = (\epsilon - 1)(g_S - g_L)$, g_f is the rate of technological progress for factor $f \in \{S, L\}$, and κ is a composite of α, ϵ and the initial levels of the technology indices[19]. As before, $\epsilon = 1/(1-\theta)$ is the elasticity of substitution between skilled-labor and unskilled-labor. This expression is very similar to what we had in the theory; the additional coefficient to time captures biased technological change[20]. Notice that although capital is in the production function, it does not appear in (7); this is due to the technology assumption embedded in (6), that of equal elasticity of substitution between capital and each type of labor. Below I discuss the implications of this assumption failing to hold.

With some identification assumptions one could estimate the elasticity of substitution by industry using (7) and time-series variation in the data. Recall that in the model each firm, or industry, is competitive and therefore takes prices as given. Suppose that firms are also small relative to the size of the economy. This amounts to an elastic relative supply of labor x at relative price π for the individual firm. So it is not a terrible sin to ignore the classic simultaneous demand-supply identification problem for an individual industry. Of course, π will be determined endogenously at the aggregate level, but we can ignore this when estimating (7) by industry.

Stock adjustment model

In reality firms might not be able to adjust their employment to desired levels (or intensity ratios) due to employment contracts or difficulty in adjusting the production

[19] $\kappa = \epsilon \ln(\alpha/(1-\alpha)) + (\epsilon - 1)\left[\ln A_S(0) - \ln A_L(0)\right]$.

[20] See Antras (2004) for a discussion of why failing to control for biased technical change may bias estimates of the elasticity of substitution. Antras focuses on aggregate capital-labor complementarity, but his argument is germane to this setting as well.

process to accommodate higher or lower skill intensity. One way to model this is with a sluggish adjustment process for labor, namely, a stock adjustment model. This captures labor market "rigidities" or difficulties in altering the production technique that might not allow firms to adjust employment to optimal levels within one period[21].

Suppose that the firm would optimally like to set it's skill intensity according to the FOC (in logs)

$$\ln x_t^* = \kappa - \epsilon \ln \pi_t + \lambda \cdot t,$$

where, as before, x is the skill intensity, π is the skill premium and κ, ϵ, and λ are given above in Equation (7). Thus x_t^* is the optimal skill intensity that would be chosen if adjustment to π_t was smooth or completed within one period. Consider the case in which the adjustment process is given by

$$(\ln x_t - \ln x_{t-1}) = (1-\delta)(\ln x_t^* - \ln x_{t-1}),$$

or

$$\ln x_t = (1-\delta) \ln x_t^* + \delta \ln x_{t-1},$$

where δ captures the "stickiness" of the adjustment process. Plugging in the expression for $\ln x_t^*$ and rearranging yields

$$\ln(x_t) = \widetilde{\kappa} - \beta \ln \pi_t + \delta \ln(x_{t-1}) + \widetilde{\lambda} \cdot t, \tag{8}$$

where $\beta = (1-\delta)\epsilon$, $\widetilde{\kappa} = (1-\delta)\kappa$ and $\widetilde{\lambda} = (1-\delta)\lambda$. Under the same identification assumptions, one can retrieve the elasticity of substitution, $\epsilon = \beta/(1-\delta)$.

4.1 Digression: capital-skill complementarity

The production function (6) imposes an equal degree of complementarity between capital and both types of labor, i.e., the same elasticity of substitution between capital and both types of labor. Admittedly, this formulation is at odds with the notion of capital-skill complementarity. Griliches (1969) finds that capital and skilled-labor are more complementary than capital and unskilled-labor. At the aggregate level Krusell et al. (2000) find a lower EoS between machinery (one kind of capital good) and skilled-labor than between machinery and unskilled-labor[22].

If this is indeed the case, then the estimates of ϵ from (7) and (8) would be biased downwards (the estimator of the coefficient to π would be biased upwards)

[21] In the data used below, one period is a year.

[22] Krusell et al. (2000) separate machinery capital from structures capital and impose that the EoS between structures and the composite of all other inputs is one.Therefore it is not clear whether the total capital stock, including both machinery and structures, is more complementary to skilled-labor relative to unskilled labor.

due to omitting a term that involves the log of capital-skill intensity. A higher skill premium not only reduces skill intensity—it increases capital-skill intensity as well. In the presence of capital-skill complementarity, an increase in capital-skill intensity is associated with an increase skill intensity, which causes the bias. See appendix for details. More importantly, there is concern that the bias may be systematically larger or smaller for skill-intensive industries.

To try to address this issue I fit below regressions of the form

$$\ln(K/S)_t = \phi^0 + \phi^1 \ln \pi_t + \phi^2 \cdot t + \xi_t,$$

where K/S is the capital-skill intensity. The ϕ^1 coefficient reflect the potential for bias due to omitting K/S in (7) and (8); if they do not exhibit any relationship with skill intensity, then the bias in (7) and (8) does not vary systematically with skill intensity. This will be tested below.

If indeed capital and skill are strong complements, then the bias will be small anyway. The intuition for this is as follows. Strong complementarity between capital and skilled labor implies that their relative demand and quantities employed will be relatively constant, so changes in the skill premium will not affect their relative demand much. For more details see appendix.

Incorporating capital-skill complementarity in a way that still allows a direct estimate of the elasticity of substitution between skilled- and unskilled-labor is beyond the scope of this paper. Therefore, the estimation does not take it into account and I proceed while taking note of this caveat.

4.2 Elasticities of substitution across industries in the North

In this section I describe the estimation procedure, data and results used to support the claim that in the North elasticities of substitution between skilled-labor and unskilled-labor are not equal and that they are higher in the skill-intensive industries. For this I use US data.

4.2.1 US: manufacturing data

The NBER-CES Manufacturing Industry Database[23] provides data on total wage bill, wage bill of production workers, total employment and employment of US production workers for 459 4-digit SIC industries in 1958-1997. Denote these series, respectively, as PAY, $PRODW$, EMP and $PRODE$. Under the 1987 SIC system, each 4-digit industry is classified into one of 140 3-digit sectors, which are then each classified into one of 20 2-digit sectors, which comprise the manufacturing sector.

[23] Bartlesman, Becker and Gray (2000). Available at http://www.nber.org/nberces/

Under the assumption that production workers are unskilled and non-production worker are skilled, one can calculate skill intensities and skill premia for all years and industries as follows:

$$\begin{aligned} x &= \frac{(EMP - PRODE)}{PRODE} \\ \pi &= \frac{(PAY - PRODW)/(EMP - PRODE)}{PRODW/PRODE}. \end{aligned}$$

In practice, I drop the first and last years due to scarce data, leaving the 1959-1996 sample—38 annual observations per industry. In addition, I drop a few observations that have non-positive values in either one of the four basic variables above, observations that have higher wage bill of production workers than the total wage bill, and observations that have higher production employment than total employment. Some additional outliers were dropped from the sample, which were characterized by extreme values of x or π relative to the trend in their respective 4-digit SIC industry.

Although the identification of production workers as unskilled and non-production workers as skilled is not perfect, it has been used extensively in the literature. Clearly, these are crude proxies for skill and unskilled labor, but better ones are not readily available at the industry level[24]. This might raise concern for biased estimates of ϵ when estimating equations like (7), due to measurement error. On one hand, if measurement error is strictly confined to the allocation of a particular non-production (production) worker to unskilled (skilled) labor, then all measurement error in π disappears. This result would come about if the wage bill of production workers is equal to the true wage of production workers (w in the model) times the number of production workers; see appendix for details. Measurement error in x alone, of course, does not bias the estimator of ϵ.

On the other hand, if this assumption on $PRODW$ fails and $PRODE$ reflects the true number of unskilled workers with error, then spurious correlation between x and π will bias estimates of ϵ towards some number, $\chi > 0$ (the estimator of the coefficient to π will be biased towards $-\chi < 0$). If the bias in $PRODE$ results in a multiplicative error in x and π, so that when logs are taken the result is additive measurement error on both sides of the equation (with opposite signs), then the bias will be towards 1 (the estimator of the coefficient to π will be biased towards -1)[25]. Either way, this bias would work against finding variation in the elasticity of substitution across industries

[24] In particular, both clerks and engineers are classified as non-production workers, while it is obvious that their skill levels are very different. Moreover, many production workers are highly skilled technichians. See Leamer (1994) for a critique of the use of this classification to proxy for skilled and unskilled workers. However, Berman, Bound and Griliches (1994) do find that this classification is a good proxy for skilled and unskilled workers in the U.S.

[25] However, given the non-linear nature of the transformation involved in π and x, this is unlikely.

and it is important to note that the bias does not vary systematically with industry skill-intensity.

If, in addition, $PRODW$ is measured with error that is uncorrelated with measurement error in $PRODE$, then π will contain an additional measurement error that will bias the estimator of ϵ towards zero. If this is the case, then the estimator of ϵ will be biased towards a number between zero and χ (the estimator of the coefficient to π will be biased towards a number between $-\chi$ and 0). Once again, this bias would work against finding variation in the elasticity of substitution and does not vary systematically with industry skill-intensity.

Ideally, one would like to use "hours worked" data instead of employment, as they represent better the labor services that are demanded by the firm, rather than how many people are employed. However, the NBER database does not provide enough information to do so.

4.2.2 US: Estimation and results

The purpose of the estimation is to gauge the variation in ϵ across industries and to check whether higher elasticities are estimated in industries with higher skill-intensity. In principle, one could estimate (7) for each 4-digit industry separately, thus obtaining 459 estimates of ϵ, one for each industry. However, in order to gain more precise estimates and a manageable number of them, I pool industries at the 2-digit level. This procedure treats each 2-digit sector as one industry, which yields 20 estimates at the 2-digit level. The number of 4-digit industries in each 2-digit sector varies considerably from 4 to 51, with a median of 18. Table 3 describes the 20 2-digit SICs and the number of industries in each[26]. Each estimate of ϵ_s for 2-digit SIC $s = 20$, 21, ...39 is obtained by fitting

$$\ln x_{it} = \kappa_s - \epsilon_s \ln \pi_{it} + \lambda_s \cdot t + u_{it}, \tag{9}$$

to panel data using pooled OLS, where i are 4-digit industries that are contained in s. Standard errors take into account clustering of the error terms at the 4-digit level.

Table 4 reports the results from estimation at the 2-digit level of disaggregation. In addition, Table 4 reports the average skill intensity in the 2-digit sector, $\overline{x}$, and the implied rate of differential technological change, $\widehat{g_S - g_L}$. Interestingly, only six 2-digit SICs exhibit a positive differential $(\widehat{g_S - g_L} > 0)$[27]. Given that unskilled labor

[26] The number of 4-digit industries in each 3-digit industry varies from 1 to 9, with a median of 3, so the 3-digit disaggregation does not differ all that much from the 4-digit disaggregation, especially since 43 3-digit SICs contain only one 4-digit industry.

[27] Given a positive trend in skill inensity and holding the skill premium fixed, a positive differential arises only when the EoS is larger than 1. The economic intuition is as follows. If technological progress improves the productivity of skilled workers, then they become more desired in the produciton

is complementary to skilled labor in most sectors ($\widehat{\epsilon} < 1$), with a positive trend in skill intensity, this implies that technological improvements in US manufacturing may have actually been more rapid for unskilled labor than for skilled labor.

Almost all the estimates of ϵ are positive and the ones that are not positive are relatively small and not statistically significant at conventional levels. The lowest positive estimate is 0.22 for SIC 31, but it is not statistically significant despite the large sample. The lowest estimate that is also statistically significant at conventional levels is 0.37 for SIC 32, and the highest is for SIC 37 at 1.68, while most are below unity. Therefore we can say hat there is considerable variation in the EoS among the 2-digit estimates.

Using the positive estimates from Table 4, Figure 4 displays a positive relationship between estimates of the EoS and average skill intensity. Fitting a regression of the positive EoS estimates to average skill intensity (and a constant) yields a positive coefficient of 1.42 with t-statistic of 3.24 and R^2 of 0.41 (17 observations). Even after dropping the outlier SIC 27 (Printing and publishing), the relationship remains statistically significant; the coefficient to skill intensity becomes 1.84 with t-statistic of 2.54 and R^2 of 0.31. Thus, we find some support for the first part of the argument, that elasticities of substitution between skilled-labor and unskilled-labor are higher in skill-intensive industries in the North.

In addition, I fit (9) using 4-digit industry fixed effects. Now each estimate of ϵ_s is obtained by fitting

$$\ln x_{it} = \kappa_i - \epsilon_s \ln \pi_{it} + \lambda_s \cdot t + u_{it}, \tag{10}$$

to panel data using fixed effects least squares, where i are 4-digit industries that are contained in s. Thus κ_i are 4-digit industry-specific fixed effects. Standard errors take into account clustering of the error terms at the 4-digit level.

Table 5 reports the results from estimation at the 2-digit level of disaggregation. All estimates of the EoS are now positive; the smallest one that is also statistically significant at conventional levels is 0.32 for SIC 34 and the largest is 0.88 for SIC 29. The estimates are much smaller than those obtained in Table 4, but some are more precise. Since all estimates of the EoS are less than one and the time trend is positive, this implies that the estimated technological differential is towards unskilled-labor in all 2-digit sectors ($\widehat{g_S - g_L} < 0$). This strengthens the finding in Table 4, that technological improvements in US manufacturing may have been more rapid for unskilled labor than for skilled labor.

The correlation between the EoS estimates here and in Table 4 is small, at 0.2, and dropping the negative estimates lowers the correlation to nill. This implies that

process; if the firm can substitute easily to skilled workers, then it will employ relatively more of them. However, if low-skill workers are complementary to skilled workers, then the firm will find it optimal to employ relatively more unskilled workers.

omitting the fixed effects is a specification error, since there are large differences in skill intensity and/or skill premia between 4-digit industries within 2-digit sectors.

Figure 5 displays the relationship between estimates of the EoS and average skill intensity. There seems to be a weak negative statistical relationship between the two. A regression of the EoS estimates on average skill intensity (and a constant) yields a negative coefficient of -0.25 with t-statistic of 1.14 and R^2 of 0.07 (20 observations). After dropping the outlier SIC 27 the relationship remains weak and statistically insignificant; the coefficient to skill intensity becomes -0.45 with t-statistic of 1.44 and R^2 of 0.1. This result does not support the postulated pattern of production in the North.

Stock adjustment model

As a robustness check for the previous result, I estimate an augmented stock adjustment version of Equation (9). As before, I estimate the model at the 2-digit level, which yields 20 estimates of the elasticity of substitution, $\epsilon = \beta/(1-\delta)$. In practice, I fit

$$\ln(x_{it}) = \widetilde{\kappa}_i - \beta_s \ln \pi_{it} + \delta_s \ln(x_{it-1}) + \widetilde{\lambda}_s \cdot t + u_t \tag{11}$$

for 20 2-digit sectors, using fixed effects for each industry, where $s = 20, 21, ...39$, denotes the 2-digit disaggregation and i is a 4-digit industry that is contained in s. As before, I take into account clustering of the error terms at the 4-digit level.

Table 6 reports the estimation results, average skill intensity in the 2-digit sector, $\overline{x}$, and the implied rate of skill biased technological change, $\widehat{g_S - g_L}$[28]. All 20 estimates of ϵ are now positive and most are statistically significant[29]. The lowest estimate that is statistically significant is is 0.73 and the highest is 2.51. Once again, we observe large variation in the estimates of the EoS. We now have 14 sectors which exhibit a positive technological change differential ($\widehat{g_S - g_L} > 0$), which somewhat contradicts the previous findings in Tables 4 and 5.

Figure 6 displays the relationship between estimates of the EoS and average skill intensity. Two outliers are clearly visible. SIC 21 (Tobacco products) exhibits a very high EoS, which was not observed above, and the estimate is not statistically significant at conventional levels[30]; and SIC 27 (Printing and publishing) has a very high skill-intensity, which is characteristic of the publishing industry[31]. After dropping these

[28] $\widehat{g_S - g_L} = \widehat{\lambda}/(\widehat{\epsilon}-1)(1-\widehat{\delta})$ is the implied annual rate at which technological progress is biased towards skilled labor.

[29] t-statistics are calculated using the delta method.

[30] SIC 21 has only four 4-digit SIC industries in it.

[31] The following 4-digit SICs are included in the 2-digit SIC 27 and have relatively very few production workers: 2711 (Newspapers), 2721 (Periodicals), 2731 (Book publishing) and 2741 (Miscellaneous publishing).

two outliers, the positive relationship between the EoS estimates and skill intensity becomes statistically significant; a regression of the EoS estimates on skill intensity (and a constant) yields a positive coefficient of 1.12 with a t-statistic of 2.07 and R^2 of 0.21. Thus, we corroborate the finding that elasticities of substitution between skilled-labor and unskilled-labor are higher in skill-intensive industries in the North.

There is, however, concern for an upward bias in some of the estimates of δ if the error term in (11) exhibits serial correlation. If so, the estimator of δ is inconsistent, as is well known. If this is the case, then estimates of the EoS in Table 6 may be upward biased and the estimates of skill biased technological change are biased upward in absolute value, since $(1 - \delta)$ appears in the denominator of both. This alone may explain the higher estimates of the EoS in Table 6 versus Table 5.

The concern is that skill-intensive industries systematically exhibit serial correlation, and/or higher serial correlation; this would cause an upward bias in the skill-intensive industries, which might cause the positive correlation in Figure 6. To address this concern I take the following route. I perform Durbin-Watson and Breush-Godfrey tests for serial correlation in the residuals of the stock adjustment model at the 4-digit SIC level. I store the estimated serial correlation from the Durbin-Watson test (ρ_{dw}) and the p-value from the Breush-Godfrey test (p_{bg}) for each industry and create an indicator function for rejecting the null, denoted by $I(p_{bg} < 0.05)$. Using the Breush-Godfrey test, the null of no serial correlation is rejected (at the conventional 5% significance level) for 126 industries out of 459 4-digit industries[32].

To check whether these are particularly skill-intensive industries I regress $I(p_{bg} < 0.05)$ on average skill-intensity and a constant; the coefficient to average skill-intensity is negative at -0.14 with a t-statistic of 2.35 and a very low R^2 of 0.012. I also fit a regression of p_{bg} to average skill-intensity and a constant; the coefficient to average skill-intensity is positive at 0.067 with a t-statistic of 1.66 and a very low R^2 of 0.006. Thus, skill-intensity is not strongly associated with finding serial correlation—if anything we are less likely to find serial correlation in the skill-intensive industries. Moreover, a regression of ρ_{dw} on skill-intensity and a constant yields a negative coefficient at -0.04 with a t-statistic of 2.36 and a very low R^2 of 0.012. Within the subsample of 126 industries in which we reject the null of no serial correlation, a regression of ρ_{dw} on skill-intensity and a constant yields a negative coefficient , at -0.025 with a t-statistic of 0.57 and an extremely low R^2 of 0.0026. Thus, the skill-intensive industries within the subsample that might exhibit serial correlation do not have higher serial correlation. To sum up, the positive correlation in Figure 6 is not likely driven by systematic serial correlation in skill-intensive industries. Moreover, higher estimates of the EoS in Table

[32] The Durbin-Watson test is not likely to be valid in presence of a lagged LHS variable; See Greene (2000), page ##### 542 #####, and references therein. Therefore, to test for serial correlation I use the Breuch-Godfrey test. However, the Durbin-Watson statistic can be used to estimate coefficient of serial correlation.

6 are more likely due to higher optimal responsiveness of firms, had they had the option to adjust freely.

Overall, the evidence is supportive of the claim that skill-intensive industries in the US (North) exhibit higher EoS between skilled and unskilled labor.

Digression: capital-skill complementarity

The production function (6) imposes an equal degree of complementarity between capital and both types of labor, i.e., the same elasticity of substitution between capital and both types of labor. Admittedly, this formulation is at odds with the notion of capital-skill complementarity. Griliches (1969) finds that capital and skilled-labor are more complementary than capital and unskilled-labor. At the aggregate level Krusell et al. (2000) find a lower EoS between machinery (one kind of capital good) and skilled-labor than between machinery and unskilled-labor[33].

If this is indeed the case, then the estimates of ϵ from (9) would be biased downwards (the estimator of the coefficient to π would be biased upwards) due to omitting a term that involves the log of capital-skill intensity. A higher skill premium not only reduces skill intensity—it increases capital-skill intensity as well. In the presence of capital-skill complementarity, higher capital-skill intensity is associated with higher skill intensity, which causes the bias (see appendix for details). This could explain the small number of negative estimates of ϵ in the results in Table 4. More importantly, there is concern that the bias may be larger for low skill-intensity industries. If this is true, then the correlations reported in Table 4 might be spurious.

To try to address this issue I fit the following set of regressions,

$$\ln(K/S)_{it} = \phi_s^0 + \phi_s^1 \ln \pi_{it} + \phi_s^2 \cdot t + \xi_{it},$$

where, as before, $s = 20, 21, ...39$, denotes the 2-digit disaggregation, i is a 4-digit industry that is contained in s, and I take into account clustering of the error terms at the 4-digit level. K/S is the capital-skill intensity (real capital stock is from the cited NBER source above). The results are reported in Table 7. The estimated ϕ_s^1 coefficients reflect the potential for bias; they do not exhibit any relationship with skill intensity in the 2-digit SIC sector; a regression of the estimates of ϕ_s^1 on average skill intensities (and a constant) yields a statistically insignificant coefficient of 0.045 and t statistic of 0.84, with an R^2 of only 0.04. Therefore, I conclude that the likelihood of spurious correlations is small.

If indeed capital and skill are strong complements, then the bias will be small. The intuition for this is as follows. Strong complementarity between capital and skilled labor

[33]Krusell et al. (2000) separate machinery capital from structures capital and impose that the EoS between structures and the composite of all other inputs is one.Therefore it is not clear whether the total capital stock, including both machinery and structures, is more complementary to skilled-labor relative to unskilled labor.

implies that their relative demand and quantities employed will be relatively constant, so changes in the skill premium will not affect their relative demand much. For more details see appendix.

Incorporating capital-skill complementarity in a way that still allows a direct estimate of the elasticity of substitution between skilled- and unskilled-labor is beyond the scope of this paper. Therefore, the estimation does not take it into account and I proceed while taking note of this caveat.

4.3 Elasticities of substitution across industries in the South

The model postulates that the skill-intensive industries in the South have lower elasticities, and that the skill-intensive industries in the South are the skill-unintensive ones in the North. To test this I use the Chilean Annual Industrial Survey in 1979-96[34] and a dataset of the Brazilian manufacturing sector in 1986-1995, which was compiled by Shikher (2004)[35]. Given the elaborate discussion of the methodology in the previous section, I will focus only on the data and results. In general, the results are somewhat supportive for the structure of the model, but not overwhelmingly so.

4.3.1 Chile: manufacturing data

The Chilean Annual Industrial Survey in 1979-96 covers 10,927 plants in total (on average 4,519 plant observations per year, that do not necessarily operate for the entire period) which are sorted according to the ISIC Revision 2 classification into 89 4-digit industries. According to this classification each 4-digit industry is classified into one of 29 3-digit sectors, which are then each classified into one of 9 2-digit sectors, which comprise the manufacturing sector[36]. The surveys are annual and they track plants over time, so that a panel can be constructed. After constructing the panel I aggregate plants by their 4-digit ISIC classification and compute wages and employment series at the 4-digit level.

The Chilean surveys classify workers into blue-collar and white-collar workers. Each category (blue, white) is broken down by sex and a few occupation sub-categories. White collar workers can be either production workers, executives or administors. Blue collar workers can be either production workers or non-production workers. I identify white-collar workers as skilled and blue-collar workers as unskilled. I sum up all white-

[34]I thanks Prof. James Tybout for providing this dataset.

[35]I thank Prof. Serge Shikher for making his data available to me.

[36]Of the total number of plants 1,830 switch their 4-digit ISIC classification at least once. Only 522 of these plants did not change their 3-digit classification. 694 plants switched their 3-digit ISIC classifications but not their 2-digit classification, and the remainder 614 plants switch their 2-digit classification as well. This is inconsequential for the analysis below as long as the classifications accurately reflect the type of activity before and after switching.

collar employment categories and denote this series as WCE, and sum up all blue-collar employment categories and denote this series as BCE. Wages and bonuses are given by white-collar and blue-collar employment; denote white-collar wages and bonuses as WCW and blue-collar wages and bonuses as BCW[37]. Thus I calculate skill intensities and skill premia for all years and industries as follows:

$$\begin{aligned} x &= \frac{WCE}{BCE} \\ \pi &= \frac{WCW/WCE}{BCW/BCE}. \end{aligned}$$

In practice, I drop 4 observations in which one of the four basic variables are non-positive. I also drop one observation from ISIC 3530 in 1986, which is an outlier in skill intensity of 58. In addition, I drop 4-digit ISIC industry 3853 which has only 2 observations, and 3122 which exhibits a strong positive relationship between skill intensity and skill premium. This leaves 1,518 observations—mostly 17 to 18 annual observations per industry[38].

4.3.2 Chile: estimation and results

As before with the US manufacturing data, it is possible to fit (7) for each 4-digit industry separately, but I choose to pool at the 3-digit level to get a manageable number of estimates of ϵ (29) and add some precision. I choose not to pool at the 2-digit level mainly because the 3-digit ISIC classifications correspond more closely to the 2-digit SIC classification which was used above, and because doing so would yield only 9 estimates, on which it will be hard to conduct statistical tests for the strength of the relationship between the EoS and skill intensity[39]. Table 8 describes the 29 3-digit ISICs and the number of industries in each.

Table 9 reports the results of estimating (9) at the 3-digit level of disaggregation. In addition, the table reports the average skill intensity in the 2-digit sector, $\overline{x}$, and the implied rate of differential technological change, $\widehat{g_S - g_L}$. All but one estimate of ϵ

[37] Bonuses are in practice a very small fraction of wages. Results are virtually indistinguishable when wages do not include bonuses.

[38] The modal 4-digit industry (64 out of 87) has 18 annual observations. Seventeen 4-digit industries have 17 annual observations. The following five 4-digit industries have less than 17 observations: isic4 3530, 3722 and 3901 have 16; 3232 has 12; 3821 has 9; and 3845 has 8 observations.

[39] In principle, one could utilize the panel at the plant level and vastly increase the number of observations, but there are some problems with doing that. First and formost, many plants—especially the smaller ones—do not change the number of employees of either kind for several years in a row; this creates lumpiness in the skill intensity variable. In addition, it shifts the main source of identification of ϵ from the time dimension to the cross-section dimension, which may be more succeptible to biases ##### REFERENCE: GRILICHES or LUCAS #####. Nevertheless, I performed the analysis using the plant level data, pooling at the 3-digit level—and the results are qulitatively simliar.

are positive. The lowest positive estimate is 0.1 for ISIC 321, but it is not statistically significant. The lowest estimate that is also statistically significant at conventional levels is 0.31 for ISIC 372, and the highest is for ISIC 385 at 1.92, while most are below unity. Therefore we can say that there is considerable variation in the EoS among the 3-digit estimates. Almost all of the estimates of the rate of differential technological change, $\widehat{g_S - g_L}$, are negative, which follows from a positive time trend in skill intensity and estimates of the EoS that are smaller than unity[40]. Again, this seems to imply that technological improvements in manufacturing in Chile may have been more rapid for unskilled labor than for skilled labor.

Using the positive estimates from Table 9, Figure 7 displays the relationship between the estimates of the EoS and average skill intensity. Fitting a regression of the positive EoS estimates to average skill intensity (and a constant) yields a very small negative coefficient of -0.13 with t-statistic of 0.32 and R^2 of 0.004 (28 observations). After dropping the outlier ISIC 385, the negative relationship becomes somewhat stronger, but remains statistically insignificant; the coefficient to skill intensity becomes -0.34 with t-statistic of 1 and R^2 of 0.04[41]. This, constitutes weak support for the claim that elasticities of substitution between skilled-labor and unskilled-labor are lower in skill-intensive industries in the South.

The results of fitting (10) using 4-digit industry fixed effects are reported in Table 10. Almost all estimates of the EoS are positive; the smallest one that is also statistically significant at conventional levels is 0.30 for SIC 381 and the largest is still 1.92 for ISIC 385. Again, almost all of the estimates of the rate of skill biased technological change, $\widehat{g_S - g_L}$, are negative.

The correlation between the EoS estimates here and in Table 9 is 0.52 and statistically significant, and dropping the negative estimate for ISIC 355 in Table 9 yields a correlation of 0.68. However, this is to be expected, since many of the estimates did not change at all because they had only one 4-digit industry under the 3-digit classification. Restricting attention to the industries that had more than one 4-digit industry under the 3-digit classification, the correlation drops to 0.30. This implies that omitting the fixed effects is a specification error, but not as serious as with the US data, since there are not as many 4-digit industries under each 3-digit ISIC in the Chilean data as there are under the 2-digit sectors in the US data.

Using the positive estimates from Table 10, Figure 8 displays the relationship between the estimates of the EoS and average skill intensity. A regression of the EoS estimates on average skill intensity (and a constant) yields a negative coefficient of

[40] The extremely large estimate of $\widehat{g_S - g_L}$ for ISIC 361 is the result of the near-unity estimate of the EoS; with a near-Cobb-Douglas production function a trend in skill intensity can only be the result of very strong biased technological change.

[41] The t-statistic is large enough to reject the null of a positive relationship at 16.5 percent significance level.

-0.35 with t-statistic of 1 and R^2 of 0.04 (29 observations). Although this is somewhat arbitrary, the fit between EoS estimates that are statistically significant and average skill intensity is much better; a regression yields a negative coefficient of -0.72 with t-statistic of 1.52 and R^2 of 0.15 (15 observations). Once again, this seems to point to weak support to my claim.

Stock adjustment model

As with the US data, I estimate an augmented stock adjustment version of Equation (9) as a robustness check. Table 11 reports the estimation results of fitting (11) to Chilean data at the 3-digit ISIC level, average skill intensity , $\overline{x}$, and the implied rate of differential technological change, $\widehat{g_S - g_L}$. All but two estimates of ϵ are now positive, but unfortunately not many are statistically significant at conventional levels[42]. The lowest estimate that is statistically significant at conventional levels is 0.33 for ISIC 381 and the highest that is statistically significant at conventional levels is 1.96 for ISIC 356. Once again, we observe large variation in the estimates of the EoS. Unlike in Table 6, here we still find that most of the estimates of differential technological change are negative.

Fitting a regression of the positive EoS estimates on skill intensity (and a constant) yields a negative coefficient of -4.7 with a t-statistic of 1.7 and R^2 of 0.10. However, this relationship is driven by the outlier estimates for ISICs 324 and 355. Figure 9 displays the relationship between the positive estimates of the EoS and average skill intensity after dropping these two outliers. After dropping these two outliers, the negative relationship between the EoS estimates and skill intensity returns to be in line with out previous results; a regression of the EoS estimates on skill intensity (and a constant) yields a positive coefficient of -0.64 with a t-statistic of 1 and R^2 of 0.04 (25 observations). Again, this is only weak support to my claim that elasticities of substitution between skilled-labor and unskilled-labor are lower in skill-intensive industries in the North.

As in the US results for the stock-adjustment model, there is concern for an upward bias in the estimator of δ if the error term in (11) exhibits serial correlation, and that this bias is systematically associated with lower skill intensity; this might cause the weak negative correlation just reported. To address this concern I take the same route described above and perform Durbin-Watson and Breush-Godfrey tests for serial correlation in the residuals of the stock adjustment model at the 4-digit ISIC level. Using the Breush-Godfrey test, the null of no serial correlation is rejected (at the conventional 5% significance level) for only 12 industries out of 87 4-digit industries in the dataset.

To check whether these are particularly low skill-intensity industries I regress the indicator for rejecting the null in the Breush-Godfrey test, $I(p_{bg} < 0.05)$, on average

[42] t-statistics are calculated using the delta method.

skill-intensity and a constant, where p_{bg} is the p-value from the Breush-Godfrey; the regression yields a virtually zero R^2. I also fit a regression of p_{bg} to average skill-intensity and a constant; the coefficient to average skill-intensity is negative at -0.18 with a t-statistic of 1.87 and R^2 of 0.04. Thus, skill-intensity is not strongly associated with finding serial correlation—if anything we are less likely to find serial correlation in the low skill-intensity industries.

A regression of ρ_{dw} on skill-intensity and a constant yields a negative coefficient of -0.1 with a t-statistic of 1.79 and R^2 of 0.04. ; this might indicate to the opposite, that lower skill intensity industries have higher estimated serial correlations, but within the subsample of 12 industries in which we reject the null of no serial correlation, a regression of ρ_{dw} on skill-intensity and a constant yields a positive coefficient of 0.04 with a t-statistic of 0.11 and an extremely low R^2 of 0.0013. Thus, the low skill-intensity industries within the subsample that might exhibit serial correlation do not have higher serial correlation. To sum up, the negative correlation in Figure 9 is not likely driven by systematic serial correlation in low skill-intensity industries.

Overall, the evidence provides weak support for the claim that skill-intensive industries in the Chile (South) exhibit lower EoS between skilled and unskilled labor. Although the results are disappointing, at least one can have some confidence in the estimation procedures, which all point in the same direction, and exhibit similar estimates across specifications, which can be observed graphically.

4.3.3 Brazil: manufacturing data

Brazilian manufacturing sector data in 1986-1995 are taken from Shikher (2004), who goes into great pains to construct series that are more accurate measures of the variables in interest; for details see his paper. Shikher uses a slightly different classification that roughly corresponds to the US SIC; this is done in order to classify as many firms as possible into one activity or the other. For example, it makes sense to aggregate SIC 22 (Textile mill products) with SIC 31 (Leather and leather products) if many firms operate in both sectors. Table 12 describes the classifications and how they correspond to the SIC. Unfortunately, finer disaggregation is not available from this source.

In line with the US manufacturing data, Shikher classifies workers into production and non-production workers. This classification is based on the original surveys used to develop his series. He provides series on their employment, $PRODE$ and $NPRODE$, and on their wages directly, $PRODW$ and $NPRODW$. Under the assumption that production workers are unskilled and non-production worker are skilled, one can calculate skill intensities and skill premia for all years and industries as follows:

$$
\begin{aligned}
x &= \frac{NPRODE}{PRODE} \\
\pi &= \frac{NPRODW}{PRODW}.
\end{aligned}
$$

4.3.4 Brazil: estimation and results

Since greater disaggregation is not available for this dataset, I fit (7) for each of Shikher's industries to get 19 estimates of ϵ. Table 13 reports the results of this estimation, average skill intensity, $\overline{x}$, and the implied rate of differential technological change, $\widehat{g_S - g_L}$. Note that the small number of observations (10) results in very inaccurate estimates. The lowest positive estimate that is also statistically significant at conventional levels is 0.53 for industry 19, and the highest is for industry 15 at 1.13, while most are below unity. Therefore we can say that there is considerable variation in the EoS here as well, although not as much as with Chile and the US. Many of the estimates of the rate of differential technological change, $\widehat{g_S - g_L}$, are negative, which follows from a positive time trend in skill intensity and estimates of the EoS that are smaller than unity.

Figure 10 displays the relationship between the positive estimates of the EoS and average skill intensity. There seems to be no correlation between the two. Considering only the EoS estimates that obtain a t-statistic higher than 1.5 and fitting a regression of these estimates average skill intensity (and a constant) yields a negative coefficient of -1.2 with t-statistic of 0.8 and R^2 of 0.11 (7 observations). Further restricting attention to the estimates that obtain a t-statistic higher than 2 and fitting the same regression yields a negative coefficient of -1.53 with t-statistic of 0.84 and R^2 of 0.19 (5 observations). Admittedly, one should be reluctant to taking this exercise seriously.

Stock adjustment model

Table 14 reports the estimation results of fitting a stock adjustment version of Equation (9) to Brazilian data. The table also reports average skill intensity , $\overline{x}$, and the implied rate of differential technological change, $\widehat{g_S - g_L}$. Most estimates of ϵ are positive, but unfortunately very few are statistically significant at conventional levels[43]. The lowest estimate that is statistically significant at conventional levels is 0.42 for industry 19 and the highest that is statistically significant at conventional levels is 1.46 for industry 15. Once again, we observe large variation in the estimates of the EoS. Half of the estimates of differential technological change are now positive.

Fitting a regression of the positive EoS estimates on skill intensity (and a constant) yields a negative coefficient of -1.17 with a t-statistic of 0.5 and R^2 of 0.02 (15

[43] t-statistics are calculated using the delta method.

observations). There is one outlier in the estimates of the EoS: 4.42 for industry 12. After dropping this estimate, Figure 11 displays the relationship between the positive estimates of the EoS and average skill intensity after dropping this outlier; a regression of the EoS estimates on skill intensity (and a constant) yields a positive coefficient of -0.9 with a t-statistic of 1 and R^2 of 0.07 (14 observations). This is only weak support to my claim that elasticities of substitution between skilled-labor and unskilled-labor are lower in skill-intensive industries in the North.

I now turn to checking whether there is concern for upward bias in the estimator of δ due to serial correlation in the error term. I take the same route described above and perform Durbin-Watson and Breush-Godfrey tests for serial correlation in the residuals of the stock adjustment model for each industry. Using the Breush-Godfrey test, the null of no serial correlation is rejected (at 10% significance level) for 2 industries: 6 and 16.[44] These industries do not have particularly low skill intensities, but I proceed to perform more systematic analysis nonetheless.

I regress the indicator for rejecting the null in the Breush-Godfrey test, $I(p_{bg} < 0.05)$, on average skill-intensity and a constant, where p_{bg} is the p-value from the Breush-Godfrey; the regression yields a virtually zero R^2. I also fit a regression of p_{bg} to average skill-intensity and a constant; the coefficient to average skill-intensity is negative at -0.2 with a t-statistic of 0.56 and R^2 of 0.02. Thus, skill-intensity is not strongly associated with finding serial correlation—if anything we are less likely to find serial correlation in the low skill-intensity industries.

A regression of ρ_{dw} on skill-intensity and a constant yields a negative coefficient of -0.27 with a t-statistic of 1.1 and R^2 of 0.07; this might indicate that lower skill intensity industries have higher estimated serial correlations, but since we reject the null of no serial correlation for only two industries at 10% significance level, this seems not likely. To sum up, the negative correlation in Figure 11 is not likely driven by systematic serial correlation in low skill-intensity industries.

Overall, the evidence provides weak support for the claim that skill-intensive industries in the Brazil (South) exhibit lower EoS between skilled and unskilled labor.

5 Prices

As mentioned in the introduction, it is important to examine whether relative prices have moved in the "right" direction, i.e., to examine whether relative prices of respective skill-intensive goods increase both in the North and in the South. Recall that these are different goods: the skill intensive good in the North is relatively skill-unintensive in the South, and vice versa. This amounts to requiring an increase in the relative price of the North's skill-intensive good in the North, and a decline in the relative price of

[44]For industry 16 the null is rejected also at the 5% significance level.

the North's skill-intensive good in the South.

In order to address whether prices of skill-intensive goods have increased in the North and decreased in the South, one needs price data on *comparable* goods in many countries. It is essential for the analysis that the goods be comparable, and in particular quality adjusted, because the analysis relies on the relative price of one good increasing in the North and decreasing in the South. Other useful information may come from independent studies that show that prices have gone in the "right" direction. Luckily, both sources are available.

Sachs and Shatz (1994) estimate that the relative price of skill-intensive manufactured goods in the US increased by 9% from 1978 to 1989[45]. This result is reinforced by Krueger (1997), who finds an additional 5% increase in this relative price from 1989 to 1995. Feenstra and Hanson (1996b) emphasize the fact that the relative price of US imports to domestic goods has fallen over time, reflecting an improvement in the terms of trade for the US. Since the US imports relatively skill-unintensive goods and has a relatively skill-intensive production mix, this reflects a relative increase in the relative prices of skill-intensive goods from the US perspective. Thus, at least for the US, relative prices have moved in the right direction. I now turn to analysis of international price data.

5.1 Methodology and data

In order to further address changes in relative prices in other countries of the world, I use the Penn World Tables Benchmark Price data[46]. These data contain purchasing power parities (PPPs) for a range of goods in several countries. All PPPs express the relative purchasing power of an "international dollar" over different goods[47]. Thus, the PPP for a particular good i in country c is defined as

$$PPP_i^c = P_i^c / P_i^*,$$

where "$*$" denotes "international dollar". All PPPs are quality-adjusted across countries, so that one can compare changes in relative PPPs over time[48]. However, using

[45] Lawrence and Slaughter (1993) find a slight decline in the relative price of skill-intensive goods in the U.S. However, Sachs and Shatz (1994) show that most of Lawrence and Slaughter's price series do not cover their entire sample and that their result is driven by computers' prices. When using consistent price series and controlling for computers, Sachs and Shatz find that skill-intensive goods' prices have increased by 9% from 1978 to 1989.

[46] Available at http://pwt.econ.upenn.edu/Downloads/benchmark/benchmark.html

[47] An "international dollar" is a theoretical currency that is used as a benchmark for comparisons. It has the same purchasing power over the GDP of the U.S. as the actual U.S. dollar over the GDP of the U.S.

[48] Gross prices for goods may include a quality component. However, the procedure used to calculate the PPPs takes into account quality. Heuristically, suppose the gross price of a good is $p = PQ$, where P is the quality-adjusted price and Q stands for quality. Then $PPP_i^c = P_i^c / P_i^*$, but not $= p_i^c / p_i^*$.

the PPP data one can only infer how the relative price in a particular country has changed with respect to the relative price in international dollars:

$$\frac{PPP^c_{i,t+1}}{PPP^c_{i,t}} = \frac{P^c_{i,t+1}/P^*_{i,t+1}}{P^c_{i,t}/P^*_{i,t}} = \frac{P^c_{i,t+1}/P^c_{i,t+1}}{P^*_{i,t+1}/P^*_{i,t}}.$$

The upshot is that we can get comparable relative prices for goods that are conceptually the same in several countries, due to quality-adjustment. Although we cannot obtain the actual increase or decrease in the relative price of a particular good, we can check whether it has increased in one country more than in another, since the benchmark is the same for all. In particular, one can examine whether the relative price of the North's skill-intensive goods has increased more in the North relative to the South. If this is indeed the case, it would support the mechanism presented in the model above.

The benchmark price data exist for five years: 1970, 1975, 1980, 1985 and 1996. Unfortunately, not all the countries were sampled in each cross section. This restricts the number of countries that may be compared. In practice I do not focus on the 1970 data because it covers only 16 countries, of which almost all are developed. For each of the remaining benchmark years I create a PPP index for a group of skill-intensive goods and a group of skill-unintensive goods for each country—according to the North's ranking of skill-intensity. The choice of the goods in each group was done to match the skill-intensity of industries in the US from the NBER database. The skill-intensive goods fall under the category of "Machinery and Equipment" and skill-unintensive goods are "Clothing and Footwear, including repairs". I am forced to include repairs—which is not a traded good—in the latter index because the 1996 benchmark does not have separate headings for repairs, but has the following headings, "Clothing including repairs" and "Footwear including repairs". Thus, "Machinery and Equipment" represents the skill-intensive good in the North, and "Clothing and Footwear, including repairs" represents the skill-unintensive good in the North. See appendix for a detailed description of the data.

The PPP indices are computed by taking weighted averages over PPPs of goods that fall into each category, where the weights are nominal expenditure shares on each good within the category, which are also available from the PWT Benchmark Price source. Thus, for a particular country and year, the indices are

$$PPP_G = \sum_{i \in G} \left(\frac{E_i}{\sum_{i \in G} E_i} \right) PPP_i,$$

where E_i denotes the expenditure on good i in the local economy and $G \in \{Skill\text{-}Intensive, Skill\text{-}Unintensive\}$. Using these indices I compute relative PPPs

$$p^c_t = PPP^c_{SI,t}/PPP^c_{SU,t}$$

for all years t and countries c for which it is feasible. This results in 34 observations in 1975, 61 observations in 1980, 64 observations in 1985 and 115 observations in 1996, which are tabulated in Table 15.

5.2 Changes in relative prices

I compute the percent change in p_t^c over three intervals leading to 1996 (1975-1996, 1980-1996 and 1985-1996). The intervals are constrained by the availability of the data and were chosen to coincide with periods during which trade liberalization has generally occurred. Formally, I compute $p_{t+s}^c/p_t^c - 1$, where t is the first year in the interval and $t+s$ is the last.

For each interval I sort the countries for which the calculation is feasible in *descending* order of the change in p. This gives a ranking of countries according to the change in the relative price of skill-intensive goods to skill-unintensive goods—from the highest (positive) change to the lowest (negative change). The number of countries in each ranking are: 30 in the 1975-1996 interval, 51 in the 1980-1996 interval and 59 in the 1985-1996 interval. Table 16 reports the full rankings.

In the 1975-1996 ranking the US comes 7^{th} highest and the U.K. comes 14^{th} in the ranking. These countries experienced the most pronounced increase in skill premia in the OECD. In general, there are few developing countries in this sample, so it is hard to conclude that developing countries experienced decreases in the relative price of the North's skill-intensive goods. In the 1980-1996 ranking the US comes 19^{th} highest and the U.K. comes a distant 32^{nd} in the ranking. This is not supportive of increases in the relative price of the North's skill-intensive goods.

However, in the 1985-1996 ranking the US comes 7^{th} highest again, which implies that in the 10 years to 1996 it experienced an increase in the relative price of Skill-intensive goods—relative to most other countries in this sample. The U.K. comes 17^{th} in the ranking, followed by Germany, Italy, Sweden and Belgium. There tend to be more developing countries at the bottom of the 1985-1996 ranking, indicating that the relative price of the North's skill-intensive goods has actually decreased in the South relative to other countries in the sample, and perhaps even decreased absolutely. However, in the 1980-1996 ranking we observe some developed European countries at the bottom, some of which are predominant exporters of skill-intensive machinery and equipment (Eaton and Kortum (2001)). Putting together the results from all three rankings might indicate that the relative price of the North's skill-intensive goods has not increased monotonously in the North during the 1975-1996 period.

Overall, this exercise does not provide very strong evidence for a monotone increase in the relative price of the North's skill-intensive goods in the North and a decrease in this price in the South over the entire 1975-1996 period. But it does provide some evidence for such an increase over the 1985-1996 period.

6 Calibration and Comparative statics

In the previous sections I have provided some supporting evidence for the postulated pattern of production and changes in relative prices. Based on estimates obtained above I now quantify the model's parameters in a reasonable way in order to see whether the model can yield similar changes in skill premia as in the data, in particular, a larger increase in the South. Another point that the exercise will make is that—given the reasonable parameter values—very small changes in goods prices can wield very large changes in relative wages. Of course, this is nothing but a manifestation of the Stolper-Samuelson Theorem, but the actual magnitudes that the exercise reveals imply that small—perhaps unoticable—changes in goods prices can wield very large changes in wages.

When choosing values for the model's parameter, one must keep in mind that this model is extremely stylized and that there are no obvious moments against which to calibrate. For instance, in the model there are only two countries engaging in trade whereas in reality there are many "Norths" and "Souths"; and there is no steady state (or average) concept for skill premia. More importantly, there are no two sectors and factors that naturally correspond to the ones in the model. I deal with this issue first.

6.1 Workers and sectors

I postulate country endowments $\overline{S}_n = 45$, $\overline{L}_n = 55$, $\overline{S}_s = 10$, $\overline{L}_s = 100$, which completes the demographic characterization of the model. In doing this I make sure that both countries are of roughly the same size, so that neither dominates the equilibrium international prices under a free trade regime[49]. The relative magnitudes of $\overline{S}_c/\overline{L}_c$ ensure that the North is skill-abundant enough to be in the "North" equilibrium depicted in Figure **??** and the South is skill-scarce enough to be in the "South" equilibrium. This means that good 1 is skill-intensive in the North, whereas good 2 is skill-intensive in the South. I assume homothetic preferences, which are represented here by Cobb-Douglas utility function $u(c_1, c_2) = c_1^{\beta} c_2^{1-\beta}$, where $\beta = 1/2$. This is an innocuous assumption that does not affect the results.

Recall that under the theoretical free trade regime the North exported good 1 and imported good 2, and that good 1 was skill intensive relative to good 2. Eaton and Kortum (2001) show that developed countries are predominant exporters of capital goods to the South. Moreover, in theory the relative price of the North's skill intensive good (good 1) increased in the North and decreased in the South. In the previous section I provided some evidence that might indicate that relative prices have changed according to this pattern.

[49] This prevents the price change from being much larger for the smaller of the two countries due to its size alone.

In what follows, I identify sector 1 with SICs 35-38: "Industrial Machinery and Equipment", "Electronic and Other Electric Equipment", "Transportation Equipment" and "Instruments and Related Products", respectively. These industries correspond to the "Machinery and Equipment" category of the price analysis above.

Sachs and Shatz (1994) find a pronounced increase in the importation of low skill-intensity manufactured goods to the US from 1978 to 1990. Therefore, I identify sector 2 as SICs 22-23: "Textile Mill Products" and "Apparel and Other Textile Mill Products", respectively. These industries are much less skill intensive than SICs 35-38, and correspond to the "Clothing and Footwear, including repairs" category of the price analysis above.

Sector 1 is locally skill-intensive in the US: the proportion of non-production to production workers is relatively high within the manufacturing sector, which can be seen in the $\overline{x}$ column in Tables 4-6. These two sectors by any means do not exhaust the entire manufacturing sector. However, they are characteristic of trade patterns between the US and other less developed countries.

This characterization of sectors assumes that sector 1 (capital goods) is *not* the locally skill-intensive in the South. Capital goods may be produced by very different input mixes, although the service they provide (in an hedonic sense) is very similar. On the other hand, light manufactures are produced with relatively similar input mixes in both countries (with $\epsilon_2 = 0$, it is the same), which makes sense, since their production methods are more standardized and "simple".

6.2 Technology parameters

6.2.1 Elasticities of substitution (ϵ_i)

Given the choice of sectors, one can take the corresponding elasticities from the estimation reported above. In Tables 6 SICs 22 and 23 have estimated elasticities of roughly 1. I choose $\epsilon_2 = 0.9$, which is a bit lower to reflect lower elasticities in other skill-unintensive sectors and for computational reasons. In the Chilean data, SICs 22 and 23 roughly correspond to ISICs 321-324 and in the Brazilian data they correspond roughly to industries 2 and 3. Unfortunately, many of the estimates are not accurate for the latter two countries.

The elasticities for SICs 35-38 in Table 6 are between 0.98 and 1.9. I choose $\epsilon_1 = 1.6$, which is roughly the average. In the Chilean data, SICs 35-38 roughly correspond to ISICs 381-385 and in the Brazilian data they correspond roughly to industries 15-18. Many of the estimates are not accurate for the latter two countries, but some estimates that are statistically significant are near 1.6. In practice, the comparative statics results hold for a wide range of elasticities that maintain the condition $\epsilon_1 > \epsilon_2$. In accordance with the theoretical model, I assume that these elasticities are the same in the North and in the South.

To put these elasticities in context, I report estimates from previous work. Fallon and Layard (1975) estimate a nested CES production function for 4 sectors, one of which is manufacturing; they estimate the elasticity between skilled-labor and unskilled-labor in the range of 0.74-1.66[50]. My chosen parameter values are in this range. At the aggregate level Fallon and Layard estimate the EoS between skilled-labor and unskilled-labor between 0.3 and 1.5. More recent estimates of the aggregate EoS between skilled-labor and unskilled-labor run between 0.67 and 2. My chosen parameter values are consistent with these aggregate ones[51].

6.2.2 Distribution parameters (α_i)

The estimation of the elasticities in (9) does not allow a direct estimation of the distribution parameters, α_i, because they are convoluted with initial levels of the technology indices in κ[52]. The following procedure for choosing values for α_i is flawed because it ignores biased technical change, but it helps gauge benchmark values for the distribution parameters.

Given the chosen values for the EoS, one can gauge the value of the distribution parameter for various industries, using the following equation,

$$\frac{\alpha_i}{1-\alpha_i} = \pi_i \cdot {x_i}^{1/\epsilon_i},$$

which follows from the firms FOCs in industry i. Using the estimated values for ϵ_i and the US data on π_i and x_i I obtain the following ranges for $\alpha_1 \in [0.41,\ 0.6]$ and $\alpha_2 \in [0.25\ ,\ 0.45]$[53]. In what follows, I take $\alpha_1 = 0.55$ and $\alpha_2 = 0.45$. These are taken to be the same in the North and in the South.

[50]Their specification does not allow a direct estimate of the EoS between skilled- and unskilled-labor. In their specification the elasticity between skilled- and unskilled labor is not constant and depends on the employed capital stock. However, it is still possible to obtain a range for the elasticity. They identify the regression from international, cross section variation, making the explicit assumption that these production functions are identical across countries.

[51]Card and Lemieux (2001) estimate the EoS between skilled-male workers and unskilled-male workers between 2 and 2.5, and between 1.1 and 1.6 for both genders. Krusell et al. (2000) estimate it between 0.67 and 1.67; Heckman, Lochner and Taber (1998) find that it is 1.44; Katz and Murphy (1992) find 1.41; Johnson (1970) finds 1.5. Johnson and Stafford (1999) note that recent studies at the aggregate level obtain a higher range for the elasticity of substitution between skilled- and unskilled labor between 1.5 and 2.

[52]Without allowing biased technical change the constant of the regresison would include only the distribution parameter and the elasticity of substitution. In this case, α is separately identified.

[53]These are ranges between the relevant 4-digit SICs that lie within the sectors Identified above.

6.2.3 Relative productivity (A_i)

Since relative productivity in a given country is not separately identified in the model from relative prices, I choose values that ensure a lower relative price of skill-intensive goods in autarky in the North[54]. Thus, for practical purposes, I postulate the following values for industries and countries: in the North, $A_{1n} = 1.1$, $A_{2n} = 1$; and in the South, $A_{1s} = 0.9$, $A_{2s} = 1$. The actual magnitudes are not so important. What is significant is that these values, together with the labor endowments, ensure $p_n^{aut} < p_s^{aut}$ and hence the observed trade patterns.

Table 17 summarizes the parameters for calibration. One should consider these parameters for heuristic purposes alone. Nevertheless, the comparative statics results hold for reasonable permutations of these parameters. We are now ready to turn to the impact of lowering trade barriers and free trade on both countries.

6.3 Comparative statics

Given the parametric choices above, I perform two comparative statics experiments: "globalization" and "tariff reduction"[55]. The first experiment considers the changes in both economies when they move from autarky to a free trade regime with no barriers or transportation costs. In the second experiment I treat each country separately as a small open economy and consider the changes in each economy when it reduces tariffs while keeping international goods prices fixed. Both experiments test the ability of the model to match qualitatively and quantitatively the stylized facts on skill premia. The first one is a more strict test because prices are endogenous; the second aims to be more realistic in the sense that tariffs are not eliminated altogether.

6.3.1 Globalization

Here I consider a process of "globalization", in which both economies move from autarky to a free trade regime with no trade barriers or transportation costs. The experiment shows that the calibrated model captures all stylized on skill premia, and in particular fact 3, namely that the skill premium increases more in the South as trade barriers are reduced. Another result is that very small changes in relative prices wield very large changes in relative wages in both countries.

[54] The NBER-CES Manufacturing Industry Database's TFP estimates are indices that are normalized to a base year and are not comparable across industries. The ICOP Industrial Database (1987 Benchmark) (Groningen Growth & Development Center, University of Groningen, available online at http://www.ggdc.net/icop.html) provides year-by-year comparable estimates of value added per worker, but not by industries. Moreover, they do not control for capital intensity.

[55] These experiments require numerical solution of the model, since the equilibrium is characterized by a system of non-linear equations with no closed-form solution. Matlab codes for computing the equilibrium and producing the graphical exposition are available upon request.

The economies start in autarky. This is illustrated in the top panels of Figure 12. The rays from the origin mark the country skill-abundance and skill-intensity in both sectors. Since both goods are demanded, then in autarky both goods are produced, which ensures $x_2 < \overline{x} < x_1$ in the North and $x_1 < \overline{x} < x_2$ in the South (recall: $x_i = S_i/L_i$ and $\overline{x} = S/L$ for each country).

The South exhibits a higher skill premium as expected, which is consistent with the first stylized fact. Given (3), the fact that $p_n^{aut} < p_s^{aut}$ and the analysis above, we can predict that the skill premium will rise in both countries when they engage in free trade (stylized fact 2). The bottom panels of Figure 12 illustrates this, but also the fact that the skill premium increases more in the South, which is stylized fact 3. The skill premium increases by 9.5 percent points in the North, and by 350 percent points in the South.

Notice that the relative price increased by only 0.5 percent points in the North, but caused a skill premium increase twenty-fold bigger. Similarly in the South, the relative price decreased by only 9 percent points and caused a much bigger skill premium increase. This is a manifestation of the Stolper-Samuelson Theorem. Due to trade liberalization both countries become very specialized in production—but not completely, so that the same conditions for equilibrium hold[56].

This last magnification result is germane to the debate on whether price changes have been large enough to induce the wage changes needed to justify the observed increases in skill premia. For instance, Lawrence and Slaughter (1993) and Sachs and Shatz (1994) have argued that the price changes of skill-intensive goods in the US could not have been large enough to explain the rise in the US economy-wide skill premium. This experiment shows how strong the magnification effect can be. If this effect is present in reality to any extent, its potential impact might be underestimated. Moreover, these claims disregard the fact that in general equilibrium wages are set at the margin. In theory, these effects will spread to other sectors, including non-tradeables. Unless labor markets are segmented enough to isolate workers from the effects of the tradeables sector, the effect will be felt in all sectors of the economy. Thus, the "tail" (relative prices) may have "wagged the dog" (economy-wide relative wages).

The same experiment is reported in the appendix for fixed-proportions production in sector 2.

6.3.2 Tariff reductions

One possible critique of the theoretical globalization experiment is that countries do not, in fact, move from complete autarky to completely free trade; they lower their

[56] That is, the experiment does not move the cone of diversification away from the endowment vector.

tariffs, usually only gradually, but do not eliminate them altogether. This is particularly true for "North-South" trade. Moreover, there are many countries engaged in trade, so that the international equilibrium price of traded goods is not drastically affected by the policy of one country. Therefore, it is useful to examine countries as "small open economies", where they do not have an impact on the international equilibrium price of traded goods.

I report the results of the "tariff reductions" experiment when sector 2 has fixed-proportions production structure. As will be soon apparent, all three stylized facts are still captured by this experiment. For heuristic purposes I modify the parametrization of the model. I impose $\epsilon_2 = 0$, and change the endowments to $\overline{S}_n = 70$, $\overline{L}_n = 70$, $\overline{S}_s = 40$, $\overline{L}_s = 100$; this way we gain a wider range for policy in the model without moving the cone of diversification away from the endowment vector. The endowment vectors keep the same considerations as before. Another modification is changing slightly the values of the substitution parameters to $\alpha_1 = 0.6$ and $\alpha_2 = 0.4$; this reduces the sensitivity of the skill premium to tariff-price changes[57]. Preferences and productivity parameters remain the same.

In both countries the skill-unintensive sector is protected: In the North it is sector 2, whereas in the South it is sector 1. The unskilled workers in each of these skill-unintensive sectors try to increase their wages by increasing the price of the good that they produce by obtaining a tariff (from the absent government)[58]. Notice that since the North has a comparative advantage in good 1, sector 1 in the South would be smaller without the tariff. The opposite is true for sector 2; since the South has a comparative advantage in good 2, sector 2 in the North would be smaller without the tariff. In both cases, the good is protected where it is produced with lower skill intensity because it faces direct competition from skill-intensive firms in the other country that produce the same good. When the tariffs are reduced the wages of unskilled workers decrease and the skill premium increases.

Figure 13 illustrates the experiment. Both countries protect their locally skill-*un*intensive sector; in the North it is sector 2, whereas in the South it is sector 1. To match casual observation, tariffs in the North are an order of magnitude smaller than in the South. However, the results are not sensitive to this at all. What is important for capturing stylized fact 3 is that the North reduces its tariffs less than the South. In the experiment here the North reduces tariffs by 5 percent-points and the South by 20 percent-points; this causes the skill premium to increase by 29 percent points in North

[57] The sensitivity is governed by the cost shares of the factors of production: the more similar they are—the more sensitive is the skill premium to price changes. These cost shares are govenred by the substitution parameters: the more similar α_1 and α_2 are, the closer the cost shares will tend to be for all ranges of prices.

[58] They do this because they understand the Stolper-Samuelson effect. In principle, skilled workers could be doing the same in the skill-intensive sectors, but I assume this away.

and by 240 percent price in the South. Once again, all stylized facts are captured in this experiment. Moreover, the price (tariff) changes are much smaller than the increases in skill premia that they induce.

7 Conclusions

I have presented here evidence that the global rise in skill premia during the 1980s and 1990s has indeed been a global phenomenon; as such, it begs explanations that are global in scope. The trade liberalization explanation offered by the standard Heckscher-Ohlin-Samuelson model has been rejected by most economists due to its counterfactual predictions for skill premia in less-developed countries after tariff reductions. In this paper I try to see how far we can go with a modified HOS model with skill-intensity reversals in explaining the global rise in skill premia. This turns out to be farther than one might expect.

The simple general equilibrium model of international trade which is presented here captures the stylized facts of global increases in skill premia, while maintaining consistency with observed trade flows. By releasing the assumption of "no factor intensity reversals" the HOS framework becomes consistent with observation on skill premia, both in developed and less-developed countries. I presented evidence on the production structure and relative prices to support the model and in order to calibrate it. The calibrated model serves to show that the magnitudes of changes of skill premia are in line with the stylized facts.

The analysis also provides a potential explanation for why less-developed countries protect their skill-*un*intensive sectors. With skill-intensity reversals, this sector might be in direct international competition with the skill-intensive sector in developed countries. In the model, the North protects its skill-unintensive sector 2 from direct competition from the South, where it is skill-intensive. Similarly, the South protects its skill-unintensive sector 1 from direct competition from the North, where it is skill-intensive.

The model shows that trade liberalization might have been a strong force behind the increase in skill premia. On the other hand, evidence that institutional changes like the decline in unionization have systematically contributed to a decline in the skill premium around the world is still fragmentary. Evidence on skill-biased technical change is indirect at best. As noted by Krugman (2000), these explanations are too much of a "deus ex machina", and make many economists feel uneasy. On the other hand, there is more hard evidence on prices and trade flows. Therefore, this paper serves as a guide: the role of trade might be large after all.

8 Appendix

8.1 PPP indices

Here I list the "basic headings" of goods from the PWT Benchmark Year tables that were used to construct the two PPP indices, $PPP^c_{SI,t}$ and $PPP^c_{SU,t}$. For each category, skill intensive (SI) "Machinery and Equipment" and skill unintensive (SU) "Clothing and Footwear, including repairs", I list the headings that were used by benchmark year. The headings reported here are exactly how they appear in the PWT Benchmark Year tables; more elaborate details were not available by the authors of the PWT tables.

Some of the "basic headings" appear twice in the Benchmark tables. Since the PPP values were different for identical headings in a particular year, I treat them as separate goods. However I list those double headings only once here.

Clothing and Footwear, including repairs

- 1975, 1980 and 1985 benchmarks: "Men's clothing", "Women's clothing", "Children's clothing", "Clothing materials & accessories", "Repair & maintenance", "Men's footwear", "Women's footwear", "Children's footwear", "Repairs to footwear".
- 1996 benchmark: "Clothing including repairs", "Footwear including repairs".

Machinery and Equipment

- 1975 benchmark: "Other machinery", "Agricultural machine", "Office equipment", "Equip. min, bld, metal", "Text, food, chem, paper", "Precision & optical", "Electr. equip, lamps", "Telecomm & electr", "Precision & optical", "Text, food, chem, paper".
- 1980 benckmark: "Mach. food, chem, pl", "Mach. metal, wood, m", "Agricultural mach", "Equip. mining & co", "Mach. food, chem, pl", "Office equip. prec", "Electr. equip, lamp", "Telecomm & electr".
- 1985 benchmark: "Mach. food, chem, pl", "Agricultural mach", "Office equip. prec", "Mach. metal, wood, m", "Equip. mining & co", "Textile machinery", "Electr. equip, lamp".
- 1996 benchmark: "Machinery & equipment".

8.2 Bias due to capital-skill complementarity

To address the direction of potential omitted variable bias one needs to determine the correlation between the omitted variable and the regressand, plus the correlation between the omitted variable and the included regressor. In terms of (9), we seek the correlation between K/S and S/L, plus the correlation between K/S and π, where K is the capital stock and S and L are described in the text. As will become apparent shortly, both correlations are positive in the face of capital-skill complementarity, thus creating a downward bias to the estimator of ϵ in (9) (upward bias to the estimator of the coefficient to π).

Consider the following nested CES production function

$$Q = \left\{\alpha \left[\delta K^{\gamma} + (1-\delta)S^{\gamma}\right]^{\theta/\gamma} + (1-\alpha)L^{\theta}\right\}^{1/\theta},$$

where I omit biased technical progress for simplicity. This production function encompasses capital-skill complementarity. $\epsilon = 1/(1-\theta)$ is the elasticity of substitution between unskilled labor and the the capital-skill composite, and denote the elasticity of substitution between skilled labor and capital by $\eta = 1/(1-\gamma)$.

Capital-skill complementarity that is stronger than capital-unskilled-labor complementarity (Griliches (1969)) requires $\eta < \epsilon$, or equivalently $\gamma < \theta$. By manipulating the first order conditions with respect to S and L, one can obtain

$$\ln\left(\frac{S}{L}\right) = \epsilon \ln\left(\frac{\alpha\delta}{1-\alpha}\right) - \epsilon \ln \pi + \epsilon \frac{\theta-\gamma}{\gamma} \ln\left[(1-\delta)\left(\frac{K}{S}\right)^{\gamma} + \delta\right], \qquad (12)$$

where, as before, $\pi = z/w$ is the skill premium, z is skilled-labor's wage, w is unskilled-labor's wage and S/L is skill intensity (denoted above as x). In equation (9) the last term is omitted. Given $\gamma < \theta$, K/S and S/L are positively correlated, since

$$\frac{\partial \ln(S/L)}{\partial \ln(K/S)} = \epsilon(\theta-\gamma)\frac{(1-\delta)(K/S)^{\gamma}}{(1-\delta)(K/S)^{\gamma}+\delta} > 0.$$

This establishes the positive correlation of the LHS in equation (9) with the omitted term.

Now, by manipulating the first order conditions with respect to S and K, one can obtain

$$\ln\left(\frac{K}{S}\right) = \eta \ln\left(\frac{1-\delta}{\delta}\right) - \eta \ln\left(\frac{r}{z}\right),$$

where r is the rental rate of capital for the firm. Since $\eta > 0$, r/z and (K/S) are negatively correlated. Naturally, $\pi = z/w$ and r/z are negatively correlated[59], so that

[59] This is ture unless w and r co-move to offset movements in z, which is not plausible. Empirircally, π and r/z are indeed negatively correlated in the NBER manufacturing data. I calculate the returns to capital by dividing the residual value added that is not attributed to labor by the capital stock: $r = (VA - PAY)/K$.

π and (K/S) are positively correlated. This establishes the positive correlation of π with the omitted term in equation (9). Putting all this together, we can see that omitting the third term in (12) will lead to a downward bias to the estimator of ϵ (upward bias in the estimaotr of the coefficient to $\ln \pi$).

Two additional notes are in order. First, if the difference between η and ϵ, or equivalently between γ and θ, is small[60], then the bias will be small as well. Second, if capital and skilled-labor are indeed strong complements, i.e. η is small, then the again the bias will be small. This is so bcause strong capital-skill complementarity reduces the responsiveness of K/S to changes in r/z, thus reducing the correlation of the omitted term in (12) with π.

8.3 Additional comparative statics

Globalization

I report here the results of the "globalization" experiment when sector 2 has fixed-proportions production structure. The point of this exercise is to provide a robustness check for the results above. As will be soon apparent, all three stylized facts are still captured in this experiment. The parametrization of the model is slightly modified. Technology parameters are now $\epsilon_2 = 0$, $\alpha_1 = 0.6$ and $\alpha_2 = 0.4$; the endowments are $\overline{S}_n = 70$, $\overline{L}_n = 70$, $\overline{S}_s = 40$, $\overline{L}_s = 100$. See discussion above in the "tariff reductions" section. Preferences and productivity parameters remain the same.

The results are presented in Figure 14. The skill premium in autarky is higher in the South. "Globalization" yields a rise of 19 percent points in the skill premium in the North, whereas it increases by 225 percent points in the South, which is consistent with stylized facts 2 and 3. The relative price in the North increases by 5 percent points; it decreases by 31 percent points in the South.

Tariff reductions

The "tariff reductions" experiment when sector 2 has an EoS of 0.9 and with the regular parametrization is reported here. Figure 15 illustrates the experiment. Both countries protect their locally skill-*un*intensive sector; in the North it is sector 2, whereas in the South it is sector 1. In the experiment here the North reduces tariffs by 1 percent point and the South by 5 percent points; this causes the skill premium to increase by 14 percent points in North and by 165 percent points in the South. Once again, all stylized facts are captured in this experiment.

[60] This means that skilled-labor is not much more complementary to capital than unskilled-labor. At the aggregate level Krusell et al. (2000) estimate $\epsilon = 1.67$ and $\eta = 0.67$, which imply $\theta - \gamma \approx 0.9$. Thus, the bias is not likely to vanish through this channel for many industries.

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Table 1: Levels of skill premia and changes in periods of trade liberalization

Country	Skilled/Unskilled concept	S.P. (year)	S.P. (year)	Change
Colombia	University/Primary education	1.92 (1986)	2.21 (1998)	0.29
Chile	University/Primary education	3 (1976)	5.2 (1991)	2.2
Costa Rica	University/Primary education	2.64 (1984)	3.1 (1992)	0.46
China	College/No-college education	1.17 (1995)	1.64 (2000)	0.47
Ghana	White-collar/Blue-collar	1.36 (1991)	3.43 (1997)	2.07
Mexico	White-collar/Blue-collar	1.93 (1984)	2.55 (1990)	0.62
US	College/High-school education	1.48 (1979)	1.84 (1996)	0.36

Notes: The following sources have all examined the skill premium in periods of trade openning: Colombia (urban households)—Attanasio et al. (2004), Costa Rica (household surveys)—Gindling and Robbins (1999), Chile (urban households)—Robbins (1994), China (household surveys)—Li and Xu (2003), Ghana (manufacturing sector)—Gorg and Strobl (2002), Mexico (manufacturing sector)—Hanson and Harrison (1999) (manufacturing sector), US (household surveys)—Acemoglu (2003).

Table 2: Skill premia, GDP and average schooling

Country	Country Code	Skill Premium	S.P. Year	Log GDP	Average Schooling	Schooling Year
Argentina	ARG	2.297	1996	11758	8.12	1995
Australia	AUS	1.224	1994	22564	10.31	1995
Belgium	BEL	1.472	1992	22873	8.43	1990
Bolivia	BOL	2.405	1997	2356	5.18	1995
Brazil	BRA	3.908	1996	7021	4.17	1995
Canada	CAN	1.368	1994	23654	11.18	1995
Chile	CHL	3.799	1996	8438	7.53	1995
Colombia	COL	4.025	1997	6473	4.68	1995
Costa Rica	CRI	2.472	1996	7181	5.82	1995
Czech Republic	CZE	1.824	1996	13307	9.29	1995
Germany	DEU	1.489	1994	23625	9.57	1995
Denmark	DNK	1.341	1992	24597	10.13	1990
Ecuador	ECU	2.069	1996	3350	6.25	1995
Spain	ESP	1.644	1990	15915	6.09	1990
Finland	FIN	1.579	1995	20706	9.82	1995
France	FRA	1.797	1994	22555	7.94	1995
United Kingdom	GBR	1.603	1997	22703	9.03	1995
Hungary	HUN	2.026	1994	9761	8.52	1995
Israel	ISR	1.415	1992	16346	9.03	1990
Italy	ITA	1.537	1995	23073	6.60	1995
Luxembourg	LUX	1.593	1994	37568	.	.
Mexico	MEX	3.162	1996	7753	6.37	1995
Netherlands	NLD	1.403	1994	22730	8.96	1995
Norway	NOR	1.310	1995	30420	11.82	1995
Panama	PAN	3.018	1997	5652	7.70	1995
Peru	PER	2.594	1997	4787	6.92	1995
Poland	POL	1.642	1995	7796	9.73	1995
Paraguay	PRY	2.939	1998	4816	5.73	1995
Slovak Republic	SVK	1.150	1992	8835	9.07	1990
Sweden	SWE	1.444	1995	21390	11.23	1995
Taiwan	TWN	1.546	1995	.	8.03	1995
Uruguay	URY	1.675	1996	8606	6.88	1995
United States	USA	1.743	1994	30131	12.18	1995
Venezuela	VEN	2.125	1996	5973	5.35	1995

Notes: Skill premia are from Fernandez et al. (2005). S.P. Year is the year in which the skill premium was estimated. GDP is PPP adjusted in constant 2000 prices from World Bank WDI online. Average Schooling is the average years of schooling in the population from Barro and Lee (2000). Schooling Year is the year in which Average Schooling is estimated.

Table 3: US manufacturing, 2-digit SICs

SIC	Description	4-digit SICs
20	Food and kindred products	49
21	Tobacco products	4
22	Textile mill products	23
23	Apparel and other textile products	31
24	Lumber and wood products	17
25	Furniture and fixtures	13
26	Paper and allied products	17
27	Printing and publishing	14
28	Chemical and allied products	29
29	Petroleum and coal products	5
30	Rubber and miscellaneous plastic products	15
31	Leather and leather products	11
32	Stone, clay and glass products	26
33	Primary metal industries	26
34	Fabricated metal products	38
35	Industrial machinery and equipment	51
36	Electronic and other electric equipment	37
37	Transportation equipment	18
38	Instruments and related products	17
39	Miscellaneous manufacturing industries	18

Note: 4-digit SICs is the number of industries classified under the corresponding 2-digit SIC sector.

Table 4: US, elasticities of substitution and average skill intensity, simple model, pooled OLS

Estimated equation: $\ln(x_{it}) = \kappa_s - \epsilon_s \ln \pi_{it} + \lambda_s \cdot t + u_{it}$

SIC2	$\widehat{\epsilon}$	$t_{\widehat{\epsilon}}$	$\widehat{\lambda}$	$t_{\widehat{\lambda}}$	Obs.	R^2	$\widehat{g_S - g_L}$	$\overline{x}$
20	1.54	(6.59)	0.002	(1.42)	1861	0.32	0.004	0.41
21	0.47	(0.64)	0.03	(3.63)	152	0.50	-0.058	0.26
22	1.06	(2.99)	0.008	(4.31)	873	0.20	0.121	0.17
23	0.52	(2.74)	0.014	(8.44)	1171	0.23	-0.029	0.18
24	0.23	(0.89)	0.012	(4.74)	646	0.11	-0.016	0.19
25	1.4	(4.2)	0.01	(4.52)	490	0.34	0.026	0.26
26	0.59	(2.37)	0.004	(3.31)	642	0.19	-0.01	0.29
27	1.6	(2.0)	0.017	(3.4)	528	0.08	0.029	1.01
28	-0.16	(0.61)	0.009	(4.93)	1102	0.07	.	0.62
29	0.87	(16.7)	0.009	(4.1)	152	0.72	-0.07	0.50
30	0.79	(1.79)	0.005	(1.84)	532	0.21	-0.022	0.29
31	0.22	(0.88)	0.012	(5.26)	418	0.16	-0.016	0.17
32	0.37	(1.85)	0.009	(5.17)	981	0.11	-0.014	0.27
33	0.43	(1.92)	0.009	(9.01)	986	0.19	-0.016	0.29
34	0.62	(1.9)	0.009	(5.95)	1444	0.12	-0.024	0.34
35	-0.39	(1.01)	0.012	(6.45)	1936	0.10	.	0.57
36	-0.47	(1.5)	0.007	(3.07)	1406	0.07	.	0.39
37	1.68	(2.85)	0.011	(4.57)	684	0.18	0.016	0.54
38	1.03	(2.22)	0.021	(5.75)	646	0.28	0.76	0.68
39	0.62	(2.4)	0.013	(5.07)	683	0.38	-0.034	0.32

Notes: Pooled OLS estimation results. Standard errors take into account clustering of the error terms at the 4-digit level. x is skill intensity, π is the skill premium and t is a time trend. $s = 20, 21, ...39$ denotes the 2-digit SIC sector and i are 4-digit SIC industries that are contained in s. Thus, κ_i are 4-digit industry fixed effects. $\widehat{g_S - g_L} = \widehat{\lambda}/(\widehat{\epsilon} - 1)$ is the implied annual rate at which technological progress is biased towards skilled labor. I drop the results of this estimate when $\widehat{\epsilon} < 0$. $\overline{x}$ is the average skill intensity in the 2-digit SIC sector over all 4-digit industries and all years.

Table 5: US, elasticities of substitution and average skill intensity, simple model, fixed effects

Estimated equation: $\ln(x_{it}) = \kappa_i - \epsilon_s \ln \pi_{it} + \lambda_s \cdot t + u_{it}$

SIC2	$\widehat{\epsilon}$	$t_{\widehat{\epsilon}}$	$\widehat{\lambda}$	$t_{\widehat{\lambda}}$	Obs.	R^2	$\widehat{g_S - g_L}$	$\overline{x}$
20	0.63	(7.83)	0.003	(1.84)	1860	0.19	-0.008	0.41
21	0.64	(1.33)	0.029	(7.23)	152	0.79	-0.081	0.26
22	0.61	(4.12)	0.008	(4.51	873	0.37	-0.02	0.17
23	0.66	(11.45)	0.014	(8.0)	1171	0.54	-0.041	0.18
24	0.56	(3.74)	0.013	(4.83)	646	0.46	-0.029	0.19
25	0.51	(6.99)	0.009	(4.99)	490	0.42	-0.017	0.26
26	0.82	(20.73)	0.004	(4.59)	639	0.46	-0.021	0.29
27	0.51	(4.35)	0.013	(5.61)	528	0.49	-0.027	1.01
28	0.49	(2.9)	0.008	(5.25)	1102	0.37	-0.016	0.62
29	0.88	(16.48)	0.009	(5.04)	190	0.71	-0.071	0.50
30	0.15	(1.05)	0.003	(2.32)	532	0.1	-0.004	0.29
31	0.66	(3.6)	0.013	(5.74)	418	0.48	-0.038	0.17
32	0.61	(9.04)	0.009	(5.23)	981	0.41	-0.023	0.27
33	0.48	(3.36)	0.009	(8.88)	986	0.43	-0.018	0.29
34	0.32	(3.56)	0.008	(7.05)	1444	0.33	-0.012	0.34
35	0.3	(1.47)	0.013	(7.2)	1936	0.36	-0.019	0.57
36	0.34	(2.17)	0.008	(3.73)	1406	0.17	-0.013	0.39
37	0.71	(3.4)	0.011	(4.88)	684	0.35	-0.037	0.54
38	0.11	(0.47)	0.018	(5.27)	646	0.54	-0.02	0.68
39	0.78	(5.64)	0.013	(4.98)	683	0.54	-0.059	0.32

Notes: Fixed effects least squares estimation results. Standard errors take into account clustering of the error terms at the 4-digit level. x is skill intensity, π is the skill premium and t is a time trend. s = 20, 21, ...39 denotes the 2-digit SIC sector and i are 4-digit SIC industries that are contained in s. Thus, κ_i are 4-digit industry fixed effects. $\widehat{g_S - g_L} = \widehat{\lambda}/(\widehat{\epsilon}-1)$ is the implied annual rate at which technological progress is biased towards skilled labor. $\overline{x}$ is the average skill intensity in the 2-digit SIC sector over all 4-digit industries and all years.

Table 6: US, elasticities of substitution and average skill intensity, stock adjustment model

Estimated equation: $\ln(x_{it}) = \kappa_i - \beta_s \ln \pi_{it} + \delta_s \ln(x_{it-1}) + \lambda_s \cdot t + u_{it}$

SIC2	$\widehat{\beta}$	$t_{\widehat{\beta}}$	$\widehat{\delta}$	$t_{\widehat{\delta}}$	$\widehat{\lambda}$	$t_{\widehat{\lambda}}$	Obs.	R^2	$\widehat{g_S - g_L}$	$\widehat{\epsilon}$	$t_{\widehat{\epsilon}}$	$\overline{x}$
20	0.44	(5.4)	0.72	(14.69)	0.001	(1.44)	1812	0.67	0.005	1.54	(2.9)	0.41
21	0.46	(13.77)	0.82	(8.27)	0.003	(0.63)	148	0.93	0.011	2.51	(1.68)	0.26
22	0.48	(3.89)	0.56	(5.81)	0.003	(2.53)	850	0.63	0.09	1.09	(2.15)	0.17
23	0.53	(8.88)	0.49	(12.25)	0.007	(6.42)	1138	0.70	0.356	1.04	(5.82)	0.18
24	0.36	(5.48)	0.66	(13.33)	0.005	(3.36)	629	0.73	0.252	1.06	(4.16)	0.19
25	0.45	(8.71)	0.38	(2.73)	0.006	(4.89)	477	0.60	-0.034	0.73	(3.7)	0.26
26	0.84	(5.24)	0.33	(2.66)	0.003	(2.93)	626	0.68	0.016	1.25	(2.89)	0.29
27	0.31	(5.32)	0.71	(7.59)	0.004	(3.26)	515	0.80	0.211	1.07	(2.01)	1.02
28	0.37	(3.32)	0.76	(18.63)	0.001	(2.58)	1073	0.74	0.01	1.52	(2.48)	0.62
29	0.69	(14.14)	0.38	(9.90)	0.005	(5.01)	185	0.78	0.078	1.1	(8.03)	0.50
30	0.11	(1.16)	0.68	(10.98)	0.001	(1.48)	555	0.49	-0.006	0.36	(1.09)	0.30
31	0.4	(2.72)	0.58	(5.59)	0.006	(3.31)	407	0.65	-0.306	0.96	(1.77)	0.17
32	0.39	(8.59)	0.65	(14.08)	0.003	(2.87)	955	0.69	0.063	1.12	(5.24)	0.27
33	0.31	(3.45)	0.58	(9.16)	0.003	(4.96)	962	0.65	-0.028	0.73	(2.55)	0.29
34	0.23	(5.05)	0.70	(22.84)	0.003	(5.51)	1406	0.67	-0.043	0.79	(4.1)	0.34
35	0.28	(4.69)	0.82	(29.18)	0.003	(6.66)	1885	0.81	0.025	1.56	(3.12)	0.57
36	0.29	(5.83)	0.82	(25.12)	0.002	(3.62)	1369	0.77	0.014	1.64	(3.27)	0.39
37	0.55	(4.78)	0.71	(12.44)	0.003	(3.31)	666	0.70	0.012	1.9	(2.74)	0.54
38	0.18	(2.65)	0.81	(21.58)	0.004	(2.76)	629	0.84	-0.805	0.98	(1.84)	0.68
39	0.5	(8.16)	0.65	(13.15)	0.004	(2.91)	665	0.79	0.025	1.44	(3.9)	0.32

Notes: Fixed effects least squares estimation results. Standard errors take into account clustering of the error terms at the 4-digit level. x is skill intensity, π is the skill premium and t is a time trend. s = 20, 21, ...39 denotes the 2-digit SIC sector and i are 4-digit SIC industries that are contained in s. Thus, κ_i are 4-digit industry fixed effects. $\widehat{\epsilon} = \widehat{\beta}/(1-\widehat{\delta})$ is the implied elasticity of substitution. $t_{\widehat{\epsilon}}$ is calculated using the delta method. $\widehat{g_S - g_L} = \widehat{\lambda}/(\widehat{\epsilon}-1)(1-\widehat{\delta})$ is the implied annual rate at which technological progress is biased towards skilled labor. $\overline{x}$ is the average skill intensity in the 2-digit SIC sector over all 4-digit industries and all years.

Table 7: US, capital intensity, skill premia and average skill intensity

Estimated equiation: $\ln(K/S)_{it} = \phi_s^0 + \phi_s^1 \ln \pi_{it} + \phi_s^2 \cdot t + \xi_{it}$

SIC2	$\widehat{\phi^1}$	$t_{\widehat{\phi^1}}$	$\widehat{\phi^2}$	$t_{\widehat{\phi^2}}$	Obs.	R^2	$\overline{x}$
20	-0.51	(1.34)	0.03	(10.56)	1861	0.21	0.41
21	-0.72	(1.04)	0.022	(4.15)	152	0.39	0.26
22	-0.67	(1.73)	0.021	(8.14)	873	0.18	0.17
23	-0.13	(0.51)	0.02	(4.41)	1171	0.13	0.18
24	-0.75	(1.5)	0.012	(2.75)	646	0.06	0.19
25	0.38	(0.7)	0.016	(4.03)	490	0.21	0.26
26	-2.74	(3.47)	0.024	(10.55)	642	0.52	0.29
27	0.55	(1.05)	0.015	(2.69)	528	0.1	1.01
28	-2.65	(6.65)	0.019	(5.16)	1102	0.37	0.62
29	-0.70	(.48)	0.031	(3.63)	152	0.17	0.50
30	0.02	(.02)	0.018	(3.79)	532	0.12	0.29
31	-0.49	(.81)	0.031	(7.15)	418	0.32	0.17
32	-1.77	(3.88)	0.017	(4.28)	981	0.24	0.27
33	-1.85	(4.7)	0.022	(5.5)	986	0.35	0.29
34	-0.77	(1.52)	0.023	(8.95)	1444	0.21	0.34
35	-0.49	(1.54)	0.028	(10.98)	1936	0.28	0.57
36	-1.55	(4.07)	0.035	(11.39)	1406	0.41	0.39
37	-0.59	(0.81)	0.019	(4.66)	684	0.1	0.54
38	0.28	(0.59)	0.023	(4.25)	646	0.28	0.68
39	-0.22	(0.31)	0.019	(4.95)	683	0.14	0.32

Notes: Pooled OLS estimation results. Robust t-statistics in parentheses. The estimation takes into account clustering of the error terms at the 4-digit level. A constant was included in all regressions, but is not reported. K/S is capital-skill intensity, π is the skill premium and t is a time trend. $s = 20, 21, ...39$ denotes the 2-digit SIC sector and i are 4-digit SIC industries that are contained in s. $\overline{x}$ is the average skill intensity in the 2-digit SIC sector over all 4-digit industries and all years.

Table 8: Chlie manufacturing, 3-digit ISICs

ISIC	Description	4-digit ISICs
311	Food manufacturing	9
312	Food manufacturing	2*
313	Beverage industries	4
314	Tobacco manufactures	1
321	Manufacture of textiles	6
322	Manufacture of wearing apparel, except footwear	1
323	Manufacture of leather and products of leather, leather substitutes and fur, except footwear and wearing apparel	3
324	Manufacture of footwear, except vulcanized or moulded rubber or plastic footwear	1
331	Manufacture of wood and wood and cork products, except furniture	3
332	Manufacture of furniture and fixtures, except primarily of metal	1
341	Manufacture of paper and paper products	3
342	Printing, publishing and allied industries	1
351	Manufacture of industrial chemicals	4
352	Manufacture of other chemical products	4
353	Petroleum refineries	1
354	Manufacture of miscellaneous products of petroleum and coal	1
355	Manufacture of rubber products	2
356	Manufacture of plastic products not elsewhere classified	1
361	Manufacture of pottery, china and earthenware	1
362	Manufacture of glass and glass products	1
369	Manufacture of other non-metallic mineral products	6
371	Iron and steel basic industries	1
372	Non-ferrous metal basic industries	3
381	Manufacture of fabricated metal products, except machinery and equipment	6
382	Manufacture of machinery except electrical	6
383	Manufacture of electrical machinery apparatus, appliances and supplies	4
384	Manufacture of transport equipment	6
385	Manufacture of professional and scientific, and measuring and controlling equipment not elsewhere classified, and of photographic and optical goods	3**
390	Other Manufacturing Industries	4

Note: 4-digit ISICs is the number of industries classified under the corresponding 3-digit ISIC Revision 2 sector. * In practice I use only one 4-digit industry under ISIC 312 since ISIC 3122 exhibits a positive relationship between skill premia and skill intensity. ** In practice I use only two 4-digit industries under ISIC 385 since ISIC 3853 has only two annual observations.

Table 9: Chile, elasticities of substitution and average skill intensity, simple model, pooled OLS

Estimated equation: $\ln(x_{it}) = \kappa_s - \epsilon_s \ln \pi_{it} + \lambda_s \cdot t + u_{it}$

ISIC3	$\widehat{\epsilon}$	$t_{\widehat{\epsilon}}$	$\widehat{\lambda}$	$t_{\widehat{\lambda}}$	Obs.	R^2	$\widehat{g_S - g_L}$	$\overline{x}$
311	0.79	(1.83)	0.001	(0.1)	162	0.18	-0.003	0.36
312	0.69	(1.86)	0.034	(4.46)	18	0.73	-0.110	0.54
313	0.65	(1.29)	0.16	(1.44)	72	0.27	-0.046	0.62
314	0.32	(1.17)	-0.001	(0.04)	18	0.17	0.001	0.79
321	0.10	(0.5)	0.026	(3.92)	107	0.20	-0.029	0.30
322	1.62	(5.61)	0.019	(3.1)	18	0.90	0.031	0.27
323	0.17	(0.68)	0.014	(0.94)	48	0.11	-0.016	0.31
324	0.57	(1.57)	0.01	(1.01)	18	0.59	-0.022	0.19
331	0.46	(2.29)	0.008	(0.83)	54	0.13	-0.016	0.14
332	0.19	(1.76)	0.016	(5.4)	18	0.67	-0.02	0.21
341	0.54	(2.35)	-0.002	(0.13)	54	0.07	0.004	0.52
342	0.81	(2.70)	0.03	(3.4)	18	0.73	-0.155	0.72
351	0.6	(6.62)	0.042	(13.35)	72	0.42	-0.106	0.76
352	0.32	(1.63)	0.015	(2.52)	72	0.16	-0.022	0.85
353	0.14	(0.37)	0.052	(1.73)	16	0.66	-0.061	0.82
354	0.52	(1.98)	0.022	(1.74)	18	0.43	-0.046	0.48
355	-0.19	(0.31)	-0.001	(0.05)	36	0.01	.	0.39
356	1.22	(4.29)	-0.005	(1.46)	18	0.65	-0.025	0.32
361	0.98	(4.59)	-0.055	(4.97)	18	0.71	3.387	0.22
362	0.23	(1.27)	0.003	(0.44)	18	0.23	-0.004	0.39
369	0.69	(5.76)	0.012	(0.71)	108	0.27	-0.040	0.43
371	0.66	(2.75)	-0.002	(0.27)	18	0.34	0.006	0.35
372	0.31	(1.96)	0.018	(2.25)	52	0.20	-0.027	0.58
381	0.14	(0.81)	0.003	(0.54)	108	0.04	-0.003	0.34
382	0.57	(6.82)	0.003	(0.16)	97	0.13	-0.007	0.49
383	0.18	(0.74)	0.01	(1.05)	68	0.04	-0.013	0.66
384	0.21	(0.78)	0.017	(0.96)	93	0.05	-0.022	0.53
385	1.92	(2.12)	0.016	(0.87)	34	0.38	0.018	0.63
390	0.13	(1.2)	0.011	(1.81)	67	0.03	-0.013	0.28

Notes: Pooled OLS estimation results. Standard errors take into account clustering of the error terms at the 4-digit level when required. x is skill intensity, π is the skill premium and t is a time trend. s = 311, 312, ...390 denotes the 3-digit ISIC sector and i are 4-digit ISIC industries that are contained in s. $\widehat{g_S - g_L} = \widehat{\lambda}/(\widehat{\epsilon} - 1)$ is the implied annual rate at which technological progress is biased towards skilled labor. I drop the results of this estimate when $\widehat{\epsilon} < 0$. $\overline{x}$ is the average skill intensity in the 3-digit ISIC sector over all 4-digit industries and all years.

Table 10: Chile, elasticities of substitution and average skill intensity, simple model, fixed effects

Estimated equation: $\ln(x_{it}) = \kappa_i - \epsilon_s \ln \pi_{it} + \lambda_s \cdot t + u_{it}$

ISIC3	$\widehat{\epsilon}$	$t_{\widehat{\epsilon}}$	$\widehat{\lambda}$	$t_{\widehat{\lambda}}$	Obs.	R^2	$\widehat{g_S - g_L}$	$\overline{x}$
311	0.27	(1.09)	0.005	(0.77)	162	0.11	-0.007	0.36
312	0.69	(1.86)	0.034	(4.46)	18	0.73	-0.110	0.54
313	0.16	(1.51)	0.16	(2.65)	72	0.39	-0.030	0.62
314	0.32	(1.17)	-0.001	(0.04)	18	0.17	0.001	0.79
321	0.04	(0.12)	0.026	(3.29)	107	0.23	-0.028	0.30
322	1.62	(5.61)	0.019	(3.1)	18	0.90	0.031	0.27
323	0.09	(0.61)	0.012	(0.84)	48	0.08	-0.013	0.31
324	0.57	(1.57)	0.01	(1.01)	18	0.59	-0.022	0.19
331	0.44	(3.54)	0.008	(0.83)	54	0.54	-0.015	0.14
332	0.19	(1.76)	0.016	(5.4)	18	0.67	-0.02	0.21
341	0.7	(2.13)	-0.005	(0.39)	54	0.26	0.017	0.52
342	0.81	(2.7)	0.03	(3.4)	18	0.73	-0.155	0.72
351	0.51	(7.65)	0.041	(12.74)	72	0.46	-0.085	0.76
352	0.32	(2.27)	0.015	(2.49)	72	0.34	-0.022	0.85
353	0.14	(0.37)	0.052	(1.73)	16	0.66	-0.061	0.82
354	0.52	(1.98)	0.022	(1.74)	18	0.43	-0.046	0.48
355	1.11	(3.35)	-0.007	(0.24)	36	0.27	-0.061	0.39
356	1.22	(4.29)	-0.005	(1.46)	18	0.65	-0.025	0.32
361	0.98	(4.59)	-0.055	(4.97)	18	0.71	3.387	0.22
362	0.23	(1.27)	0.003	(0.44)	18	0.23	-0.004	0.39
369	0.05	(0.73)	0.034	(3.68)	108	0.43	-0.036	0.43
371	0.66	(2.75)	-0.002	(0.27)	18	0.34	0.006	0.35
372	0.40	(1.36)	0.015	(1.16)	52	0.23	-0.025	0.58
381	0.30	(1.99)	-0.0002	(0.62)	108	0.09	0.0004	0.34
382	0.38	(2.02)	0.001	(0.05)	97	0.07	-0.002	0.49
383	0.27	(1.31)	0.01	(0.98)	68	0.13	-0.014	0.66
384	0.52	(3.73)	0.005	(0.31)	93	0.09	-0.011	0.53
385	0.49	(0.39)	0.033	(2.82)	34	0.46	-0.065	0.63
390	0.17	(0.49)	0.010	(1.46)	67	0.06	-0.012	0.28

Notes: Fixed effects estimation results. Standard errors take into account clustering of the error terms at the 4-digit level when required. x is skill intensity, π is the skill premium and t is a time trend. s = 311, 312, ...390 denotes the 3-digit ISIC sector and i are 4-digit ISIC industries that are contained in s. $\widehat{g_S - g_L} = \widehat{\lambda}/(\widehat{\epsilon} - 1)$ is the implied annual rate at which technological progress is biased towards skilled labor. $\overline{x}$ is the average skill intensity in the 3-digit ISIC sector over all 4-digit industries and all years.

Table 11: Chile, elasticities of substitution and average skill intensity, stock adjustment model

Estimated equation: $\ln(x_{it}) = \kappa_i - \beta_s \ln \pi_{it} + \delta_s \ln(x_{it-1}) + \lambda_s \cdot t + u_{it}$

ISIC2	$\widehat{\beta}$	$t_{\widehat{\beta}}$	$\widehat{\delta}$	$t_{\widehat{\delta}}$	$\widehat{\lambda}$	$t_{\widehat{\lambda}}$	Obs.	R^2	$\widehat{g_S - g_L}$	$\widehat{\epsilon}$	$t_{\widehat{\epsilon}}$	$\overline{x}$
311	0.22	(0.98)	0.54	(8.96)	0.005	(1.35)	153	0.31	-0.021	0.47	(0.98)	0.36
312	0.72	(1.83)	0.17	(0.56)	0.03	(2.24)	17	0.72	-0.29	0.88	(1.5)	0.54
313	0.25	(2.57)	0.42	(2.85)	0.011	(0.9)	68	0.37	-0.034	0.42	(1.7)	0.62
314	0.42	(1.52)	-0.71	(1.53)	-0.008	(0.42)	17	0.28	0.006	0.25	(1.3)	0.79
321	-0.03	(0.12)	0.36	(2.5)	0.022	(2.6)	100	0.31	.	-0.05	(0.12)	0.30
322	1.13	(3.71)	0.57	(2.84)	0.008	(1.12)	17	0.93	0.011	2.63	(1.52)	0.27
323	0.07	(0.67)	0.32	(2.2)	0.012	(1.11)	44	0.16	-0.019	0.1	(0.78)	0.31
324	0.42	(1.36)	0.97	(2.81)	-0.002	(0.2)	17	0.72	-0.005	14.4	(0.08)	0.19
331	0.48	(2.63)	0.35	(8.71)	0.009	(0.89)	51	0.56	-0.52	0.74	(2.55)	0.14
332	0.19	(1.64)	-0.12	(0.46)	0.019	(3.67)	17	0.67	-0.02	0.17	(1.5)	0.21
341	0.65	(1.58)	0.23	(1.78)	-0.008	(0.69)	51	0.25	0.064	0.84	(1.26)	0.52
342	0.65	(1.61)	0.28	(1.04)	0.023	(1.87)	17	0.71	-0.33	0.9	(0.12)	0.72
351	0.48	(20.4)	0.16	(1.02)	0.038	(7.31)	68	0.46	-0.105	0.57	(6.32)	0.76
352	0.31	(2.41)	0.42	(6.2)	0.005	(3.0)	68	0.44	-0.018	0.54	(2.5)	0.85
353	-0.31	(0.5)	0.54	(1.23)	0.055	(1.52)	14	0.69	.	-0.67	(0.58)	0.82
354	0.51	(1.49)	0.01	(0.04)	0.022	(1.37)	17	0.36	-0.046	0.52	(1.18)	0.48
355	1.22	(3.96)	0.8	(8.02)	0.005	(0.51)	34	0.67	0.004	6.16	(1.32)	0.39
356	0.09	(4.08)	0.44	(2.24)	-0.002	(0.58)	17	0.70	-0.004	1.95	(2.08)	0.32
361	0.01	(4.36)	0.18	(0.91)	-0.045	(2.74)	17	0.69	-0.244	1.22	(3.28)	0.22
362	0.14	(0.74)	-0.19	(0.71)	0.002	(0.32)	17	0.17	-0.002	0.12	(0.79)	0.39
369	0.03	(0.37)	0.47	(5.63)	0.022	(4.77)	102	0.54	-0.044	0.06	(0.39)	0.43
371	0.65	(2.44)	0.13	(0.26)	0.001	(0.06)	17	0.32	-0.003	0.74	(1.35)	0.35
372	0.43	(2.95)	0.48	(9.19)	0.014	(2.61)	49	0.45	-0.156	0.82	(2.28)	0.58
381	0.28	(1.81)	0.14	(3.13)	0.000	(0.02)	102	0.10	0.000	0.33	(1.73)	0.34
382	0.27	(1.89)	0.27	(1.34)	0.004	(0.32)	89	0.16	-0.01	0.38	(2.09)	0.49
383	0.21	(0.9)	0.19	(3.38)	0.005	(0.69)	60	0.08	-0.008	0.26	(0.96)	0.66
384	0.54	(4.08)	0.56	(4.4)	0.016	(0.83)	81	0.21	0.148	1.24	(4.38)	0.53
385	0.37	(028)	-0.1	(3.89)	0.035	(2.69)	30	0.36	-0.048	0.33	(0.28)	0.63
390	0.19	(0.6)	0.35	(2.37)	0.008	(0.9)	58	0.18	-0.18	0.29	(0.67)	0.28

Notes: Fixed effects least squares estimation results. Standard errors take into account clustering of the error terms at the 4-digit level when required. x is skill intensity, π is the skill premium and t is a time trend. s = 311, 312, ...390 denotes the 3-digit ISIC sector and i are 4-digit ISIC industries that are contained in s. Thus, κ_i are 4-digit industry fixed effects. $\widehat{\epsilon} = \widehat{\beta}/(1 - \widehat{\delta})$ is the implied elasticity of substitution. $t_{\widehat{\epsilon}}$ is calculated using the delta method. $\widehat{g_S - g_L} = \widehat{\lambda}/(\widehat{\epsilon} - 1)(1 - \widehat{\delta})$ is the implied annual rate at which technological progress is biased towards skilled labor. I drop the results of this estimate when $\widehat{\epsilon} < 0$. $\overline{x}$ is the average skill intensity in the 3-digit ISIC sector over all 4-digit industries and all years.

Table 12: Shikher (2004) industrial clssification and corresponding SICs

Industry	Description	SIC
1	Food and kindred products except coffee and sugar	20
.	Coffee*	.
.	Sugar*	.
2	Textile mill products	22
3	Apparel and leather	23, 31
4	Lumber and wood	24
5	Furniture and fixtures	25
6	Paper and allied products	26
7	Printing and publishing	27
8	Industrial chemicals and synthetics	281, 282, 286
9	Pharmaceuticals	283
10	Residual of chemicals	284, 285, 287, 289
11	Petroleum and coal products	29
12	Rubber and rubber products	30
13	Non-metallic mineral products	32
14	Metallurgy and metal products	33, 34
15	Non-electrical machinery	35
16	Electrical and electronic machinery	36
17	Motor vehicles and equipment	371
18	Other transportation equipment	372-6, 379
19	Other industries	38, 39

Notes: Table reproduced from Shikher (2004), his Table 1. Shikher's classifications are meant to classify as many firms as possible into one activity or the other. * These data exists for Brazil but were not provided (industries Coffee and Sugar do not exist as such in the SIC).

Table 13: Brasil, elasticities of substitution and average skill intensity, simple model, pooled OLS

Estimated equation: $\ln(x_t) = \kappa_s - \epsilon_s \ln \pi_t + \lambda_s \cdot t + u_t$

Industry	$\widehat{\epsilon}$	$t_{\widehat{\epsilon}}$	$\widehat{\lambda}$	$t_{\widehat{\lambda}}$	Obs.	R^2	$\widehat{g_S - g_L}$	$\overline{x}$
1	-0.34	(0.56)	0.018	(2.9)	10	0.55	.	0.52
2	0.23	(0.84)	0.015	(3.73)	10	0.83	-0.02	0.22
3	0.37	(0.74)	0.023	(3.0)	10	0.65	-0.036	0.19
4	1.06	(5.28)	-0.02	(2.34)	10	0.80	-0.309	0.20
5	0.27	(1.21)	0.01	(0.87)	10	0.53	-0.013	0.22
6	0.74	(1.38)	-0.017	(1.75)	10	0.54	0.065	0.39
7	-0.04	(0.1)	-0.011	(0.95)	10	0.17	.	0.86
8	1.11	(2.49)	0.0	(0.06)	10	0.67	-0.004	0.38
9	-0.27	(0.26)	0.002	(0.04)	10	0.14	.	0.92
10	-0.03	(0.07)	-0.021	(2.67)	10	0.71	.	0.65
11	0.08	(0.25)	-0.023	(1.37)	10	0.24	0.025	0.52
12	0.54	(1.13)	-0.009	(0.5)	10	0.44	0.02	0.33
13	0.01	(0.06)	0.021	(6.5)	10	0.86	-0.022	0.29
14	0.62	(1.87)	-0.02	(3.96)	10	0.69	0.053	0.31
15	1.13	(4.19)	0.031	(5.16)	10	0.81	0.245	0.36
16	0.55	(3.46)	0.007	(1.43)	10	0.63	-0.016	0.44
17	-0.37	(0.46)	-0.05	(1.71)	10	0.74	.	0.32
18	0.87	(1.9)	-0.014	(1.35)	10	0.47	0.114	0.30
19	0.53	(2.68)	0.012	(2..24)	10	0.79	-0.025	0.36

Notes: OLS estimation results. x is skill intensity, π is the skill premium and t is a time trend. $s = 1, 2, ...21$ denotes the sector. $\widehat{g_S - g_L} = \widehat{\lambda}/(\widehat{\epsilon} - 1)$ is the implied annual rate at which technological progress is biased towards skilled labor. I drop the results of this estimate when $\widehat{\epsilon} < 0$. $\overline{x}$ is the average skill intensity in the sector over all years.

Table 14: Brasil, elasticities of substitution and average skill intensity, stock adjustment model

Estimated equation: $\ln(x_t) = \kappa_s - \beta_s \ln \pi_t + \delta_s \ln(x_{t-1}) + \lambda_s \cdot t + u_t$

Ind.	$\widehat{\beta}$	$t_{\widehat{\beta}}$	$\widehat{\delta}$	$t_{\widehat{\delta}}$	$\widehat{\lambda}$	$t_{\widehat{\lambda}}$	Obs.	R^2	$\widehat{g_S - g_L}$	$\widehat{\epsilon}$	$t_{\widehat{\epsilon}}$	$\overline{x}$
1	-0.32	(0.55)	0.77	(1.92)	-0.001	(0.1)	9	0.69	.	-1.37	(0.38)	0.52
2	0.28	(0.8)	0.55	(1.47)	0.004	(0.51)	9	0.83	-0.013	0.62	(0.83)	0.22
3	0.28	(0.43)	0.25	(0.57)	0.017	(1.14)	9	0.59	-0.031	0.37	(0.39)	0.19
4	1.24	(3.46)	-0.23	(0.79)	-0.022	(2.22)	9	0.81	-0.076	1.01	(2.02)	0.20
5	0.11	(0.44)	0.47	(1.08)	-0.001	(0.06)	9	0.49	0.002	0.21	(0.37)	0.22
6	0.51	(1.16)	0.42	(1.48)	-0.02	(1.92)	9	0.79	0.069	0.88	(0.92)	0.39
7	-0.26	(0.73)	0.38	(1.05)	-0.023	(1.93)	9	0.59	.	-0.42	(0.63)	0.86
8	1.16	(1.79)	-0.04	(0.07)	-0.002	(0.15)	9	0.63	-0.011	1.12	(1.07)	0.38
9	-1.0	(0.83)	0.97	(1.92)	-0.021	(0.41)	9	0.58	.	-32.06	(0.06)	0.92
10	0.07	(0.17)	0.16	(0.38)	-0.021	(1.32)	9	0.81	0.026	0.08	(0.18)	0.65
11	0.02	(0.05)	0.66	(1.73)	-0.02	(0.23)	9	0.45	-0.015	0.05	(0.05)	0.52
12	0.89	(2.69)	0.8	(3.27)	0.005	(0.56)	9	0.85	-0.394	4.42	(0.9)	0.33
13	-0.04	(0.19)	0.4	(0.92)	0.009	(1.01)	9	0.84	.	-0.06	(0.2)	0.29
14	0.53	(0.92)	0.08	(0.15)	0.011	(1.99)	9	0.68	0.045	0.58	(0.67)	0.31
15	1.06	(3.17)	0.28	(1.09)	-0.019	(2.12)	9	0.79	0.601	1.46	(1.84)	0.36
16	0.17	(0.71)	0.32	(1.09)	0.024	(0.89)	9	0.65	0.013	0.25	(0.58)	0.44
17	0.01	(0.01)	-0.36	(0.84)	-0.007	(1.73)	9	0.77	0.066	0.004	(0.005)	0.32
18	0.13	(0.32)	0.7	(2.47)	-0.089	(2.61)	9	0.83	0.085	0.42	(0.26)	0.30
19	0.57	(2.74)	-0.36	(1.29)	-0.022	(2.26)	9	0.79	-0.028	0.42	(2.19)	0.36

Notes: OLS estimation results. x is skill intensity, π is the skill premium and t is a time trend. $s = 1, 2, \ldots 19$ denotes the sector. $\widehat{\epsilon} = \widehat{\beta}/(1-\widehat{\delta})$ is the implied elasticity of substitution. $t_{\widehat{\epsilon}}$ is calculated using the delta method. $\widehat{g_S - g_L} = \widehat{\lambda}/(\widehat{\epsilon}-1)(1-\widehat{\delta})$ is the implied annual rate at which technological progress is biased towards skilled labor. I drop the results of this estimate when $\widehat{\epsilon} < 0$. $\overline{x}$ is the average skill intensity in the sector over all years.

Table 15: Country benchmark PPP observations by year

1975 (N=34)

Austria, Belgium, Brazil, Colombia, Denmark, France, Germany, Hungary, India, Iran, Ireland, Italy, Jamaica, Japan, Kenya, Korea Rep., Luxembourg, Malawi, Malaysia, Mexico, Netherlands, Pakistan, Philippines, Poland, Romania, Serbia and Montenegro, Spain, Sri Lanka, Syrian Arab Republic, Thailand, United Kingdom, United States, Uruguay, Zambia

1980 (N=61)

Argentina, Austria, Belgium, Bolivia, Botswana, Brazil, Cameroon, Canada, Chile, Colombia, Costa Rica, Cote d'Ivoire, Denmark, Dominican Republic, Ecuador, El Salvador, Ethiopia, Finland, France, Germany, Greece, Guatemala, Honduras, Hong Kong, Hungary, India, Indonesia, Ireland, Israel, Italy, Japan, Kenya, Korea Rep., Luxembourg, Madagascar, Malawi, Mali, Mexico, Morocco, Netherlands, Nigeria, Norway, Pakistan, Panama, Paraguay, Peru, Philippines, Poland, Portugal, Senegal, Serbia and Montenegro, Spain, Sri Lanka, Tanzania, Tunisia, United Kingdom, United States, Uruguay, Venezuela RB, Zambia, Zimbabwe

1985 (N=64)

Australia, Austria, The Bahamas, Bangladesh, Barbados, Belgium, Benin, Botswana, Cameroon, Canada, Congo Rep., Cote d'Ivoire, Denmark, Egypt, Ethiopia, Finland, France, Germany, Greece, Grenada, Hong Kong, Hungary, India, Iran, Ireland, Italy, Jamaica, Japan, Kenya, Korea Rep., Luxembourg, Madagascar, Malawi, Mali, Mauritius, Morocco, Nepal, Netherlands, New Zealand, Nigeria, Norway, Pakistan, Philippines, Poland, Portugal, Rwanda, Senegal, Serbia and Montenegro, Sierra Leone, Spain, Sri Lanka, St. Lucia, Suriname, Swaziland, Sweden, Tanzania, Thailand, Trinidad and Tobago, Tunisia, Turkey, United Kingdom, United States, Zambia, Zimbabwe

1996 (N=115)

Albania, Antigua and Barbuda, Argentina, Armenia, Australia, Austria, Azerbaijan, The Bahamas, Bahrain, Bangladesh, Barbados, Belarus, Belgium, Belize, Benin, Bermuda, Bolivia, Botswana, Brazil, Bulgaria, Cameroon, Canada, Chile, Congo Rep., Cote d'Ivoire, Croatia, Czech Republic, Denmark, Dominica, Ecuador, Egypt, Estonia, Fiji, Finland, France, Gabon, Georgia, Germany, Greece, Grenada, Guinea, Hong Kong, Hungary, Iceland, Indonesia, Iran, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Korea Rep., Kyrgyz Republic, Latvia, Lebanon, Lithuania, Luxembourg, Macedonia FYR, Madagascar, Malawi, Mali, Mauritius, Mexico, Moldova, Mongolia, Morocco, Nepal, Netherlands, New Zealand, Nigeria, Norway, Oman, Pakistan, Panama, Peru, Philippines, Poland, Portugal, Qatar, Romania, Russian Federation, Senegal, Sierra Leone, Singapore, Slovak Republic, Slovenia, Spain, Sri Lanka, St. Kitts and Nevis, St. Lucia, Vincent and the Grenadines, Swaziland, Sweden, Switzerland, Syrian Arab Republic, Tajikistan, Tanzania, Thailand, Trinidad and Tobago, Tunisia, Turkey, Turkmenistan, Ukraine, United Kingdom, United States, Uruguay, Uzbekistan, Venezuela RB, Vietnam, Yemen Rep., Zambia, Zimbabwe

Table 16: Country rankings of relative PPP changes by inteval

1975-1996 (N=30)

Kenya, Brazil, Romania, Zambia, Syrian Arab Republic, Malawi, United States, Hungary, Denmark, Iran, France, Ireland, Poland, United Kingdom, Mexico, Japan, Jamaica, Netherlands, Uruguay, Italy, Belgium, Spain, Germany, Luxembourg, Austria, Thailand, Pakistan, Philippines, Sri Lanka, Korea Rep.

1980-1996 (N=51)

Venezuela RB, Ecuador, Botswana, Brazil, Zambia, Kenya, Tanzania, Uruguay, Bolivia, Zimbabwe, Hungary, Malawi, Poland, Nigeria, Finland, Morocco, Indonesia, Chile, United States, Cote d'Ivoire, Denmark, Madagascar, Senegal, Mexico, Norway, Peru, Canada, Netherlands, Spain, Panama, Luxembourg, United Kingdom, Germany, Ireland, Japan, Portugal, Belgium, Tunisia, Austria, Italy, France, Greece, Argentina, Israel, Philippines, Cameroon, Korea Rep., Pakistan, Mali, Hong Kong, Sri Lanka

1985-1996 (N=64)

Nepal, Tanzania, Hungary, Poland, Iran, Turkey, United States, Australia, Nigeria, Finland, Barbados, Austria, Norway, Cote d'Ivoire, Philippines, St. Lucia, United Kingdom, Denmark, Germany, Italy, Sweden, Belgium, Trinidad and Tobago, Spain, Zimbabwe, Kenya, Luxembourg, Bangladesh, France, Egypt, Ireland, Netherlands, Malawi, Greece, Hong Kong, Botswana, Tunisia, Canada, The Bahamas, Jamaica, Japan, Portugal, Grenada, Swaziland, Zambia, Thailand, Mali, Sri Lanka, New Zealand, Senegal, Mauritius, Morocco, Korea Rep., Pakistan, Benin, Madagascar, Sierra Leone, Cameroon, Congo Rep.

Notes: Each panel lists the ranking of countries according to the change in their relative PPP, $p^c_{t+s}/p^c_t - 1$, where t is the first year in the interval and $t + s$ is the last. The rankings are in ascending order, from lowest change over the interval—to the highest.

Table 17: Calibrated parameters

Demographics		Preferences		Technology		Productivity	
$\overline{S}_n$	45	β	1/2	α_1	0.55	A_{1n}	1.1
$\overline{L}_n$	55			α_2	0.45	A_{2n}	1
$\overline{S}_s$	10			ϵ_1	1.6	A_{1s}	0.9
$\overline{L}_s$	100			ϵ_2	0.9	A_{2s}	1

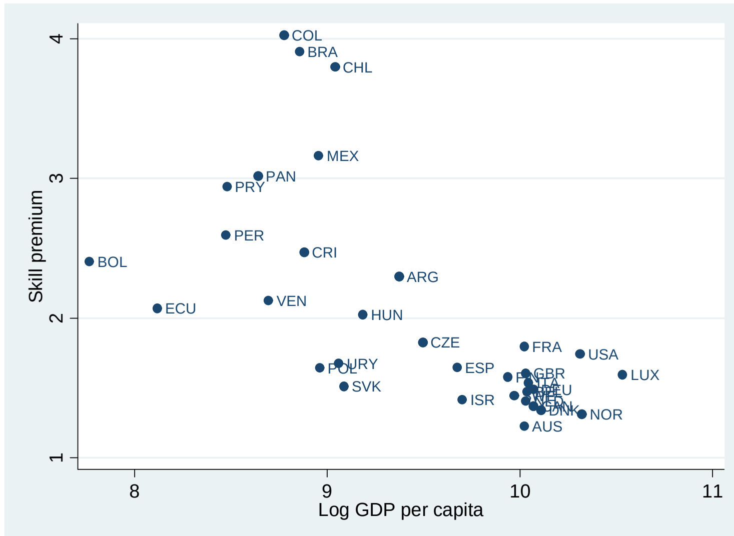

Figure 1: Skill premia and GDP in the 1990s

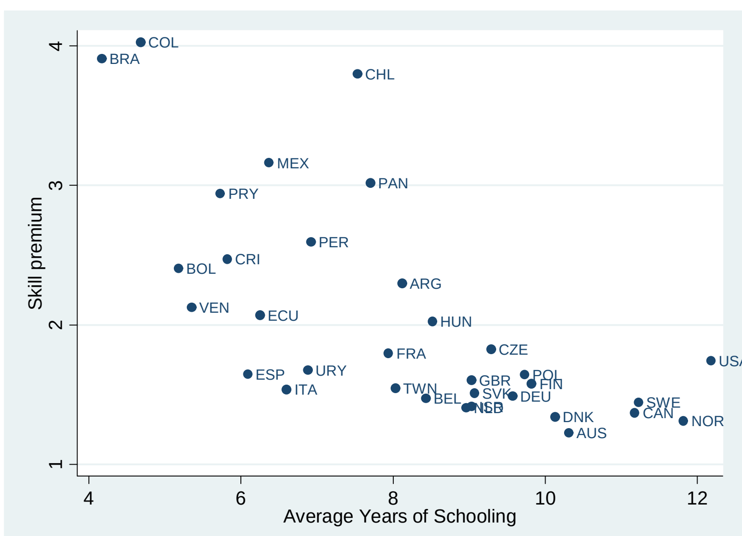

Figure 2: Skill premia and average years of schooling in the 1990s

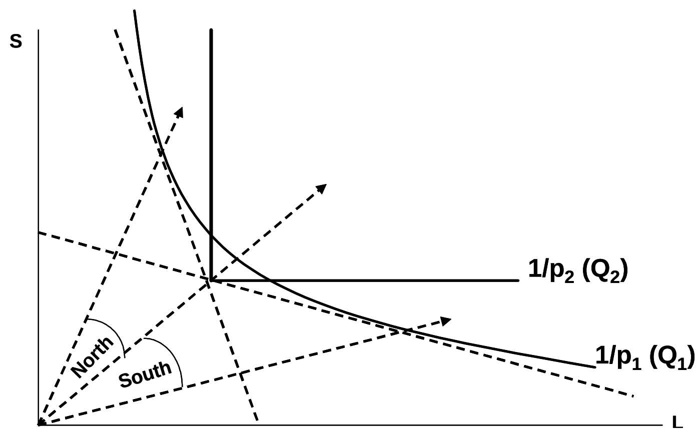

Figure 3: Skill intensity reversals

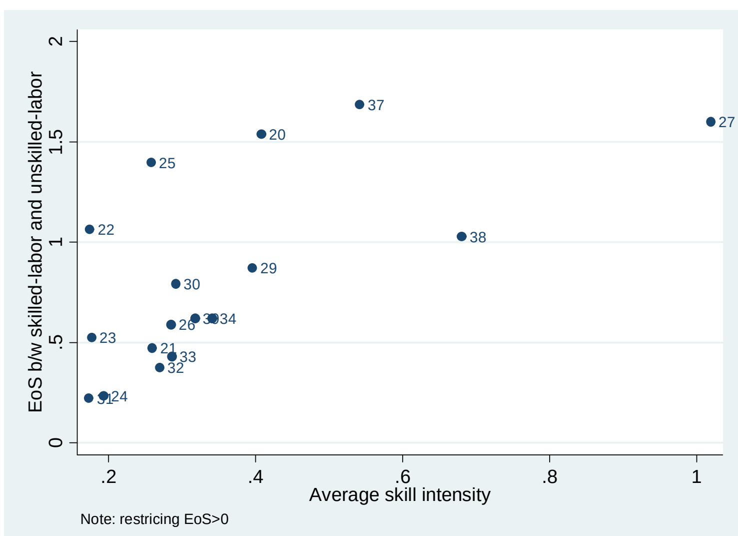

Figure 4: Elasticities of substitution and skill intensities in U.S. manufacturing, simple model

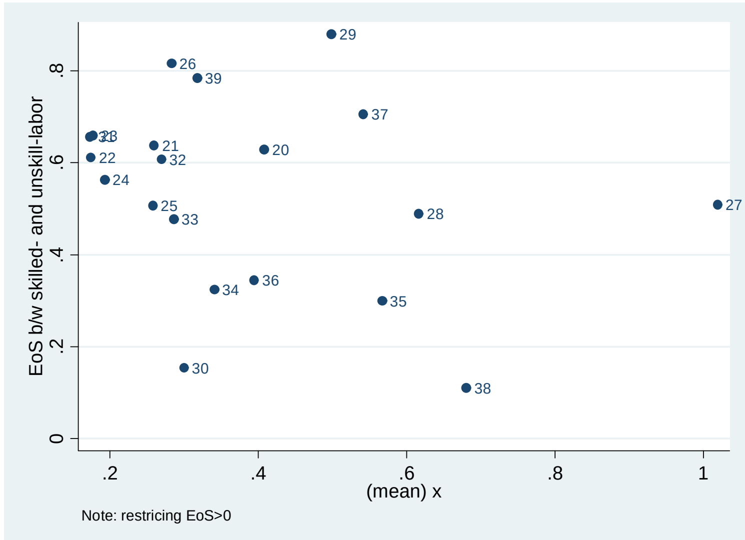

Figure 5: Elasticities of substitution and skill intensities in U.S. manufacturing, fixed effects

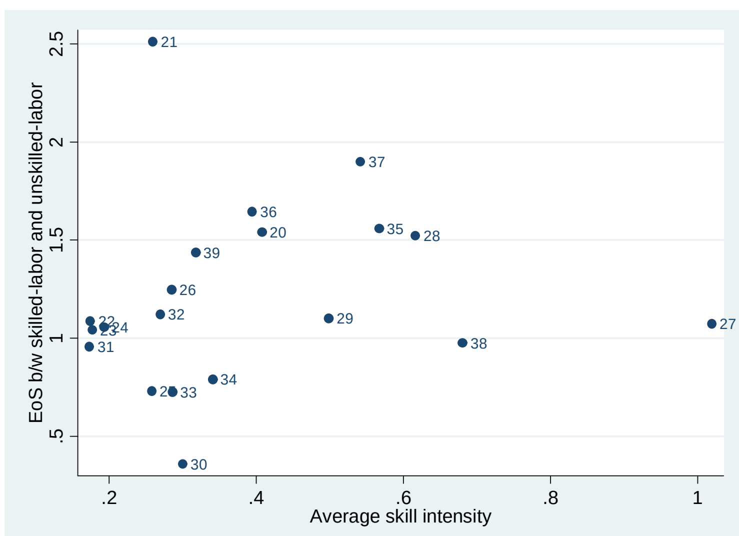

Figure 6: Elasticities of substitution and skill intensities in U.S. manufacturing, stock-adjustment model

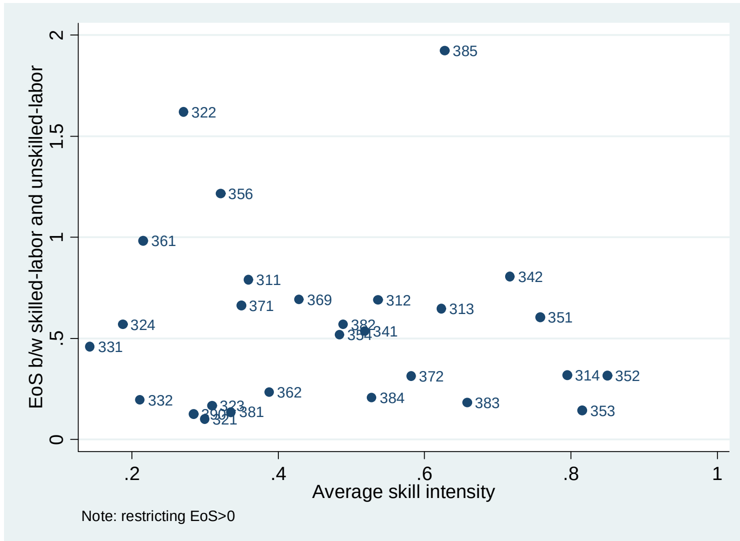

Figure 7: Elasticities of substitution and skill intensities in Chilean manufacturing, simple model

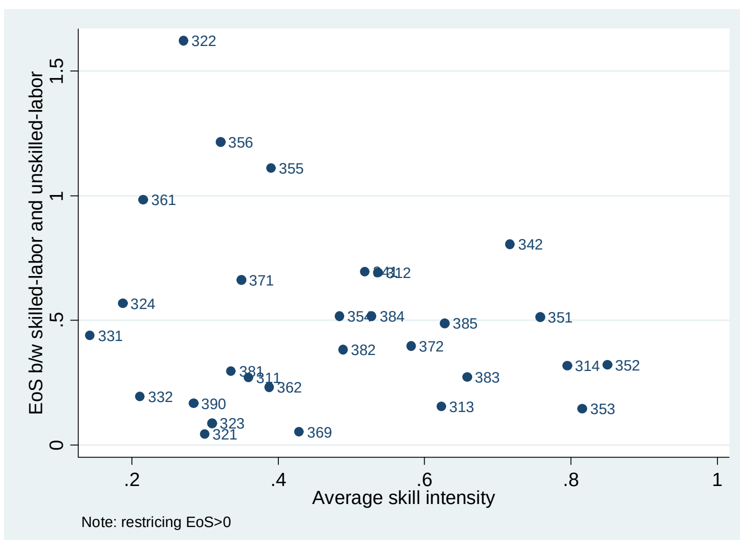

Figure 8: Elasticities of substitution and skill intensities in Chilean manufacturing, fixed effects

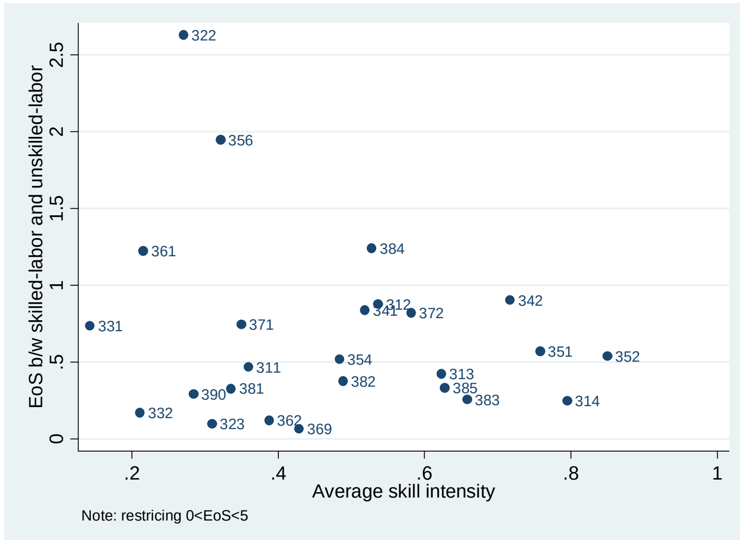

Figure 9: Elasticities of substitution and skill intensities in Chilean manufacturing, stock adjustment model

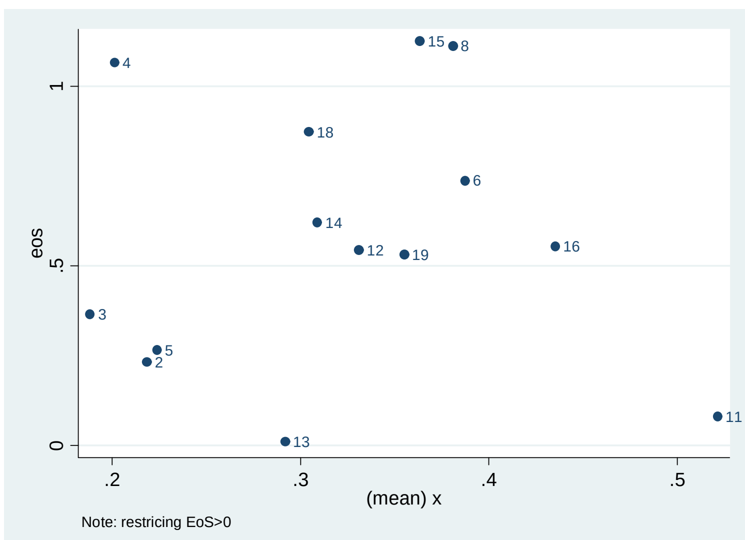

Figure 10: Elasticities of substitution and skill intensities in Brasilean manufacturing, simple model

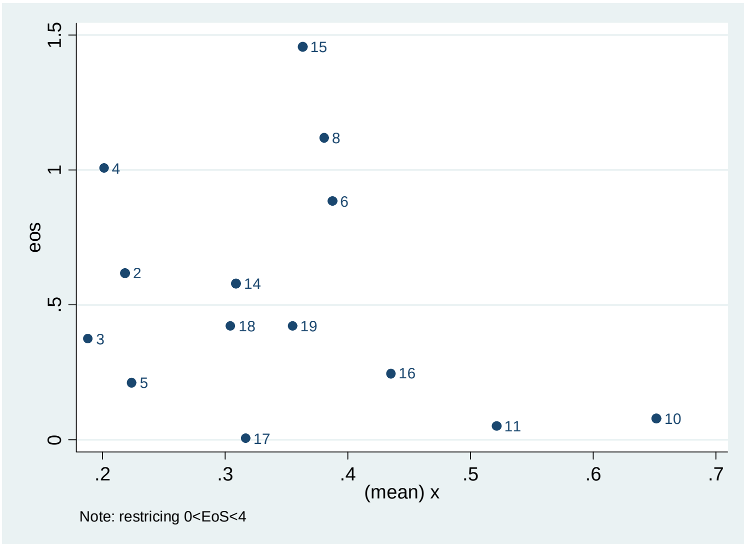

Figure 11: Elasticities of substitution and skill intensities in Brasilean manufacturing, stock adjustment model

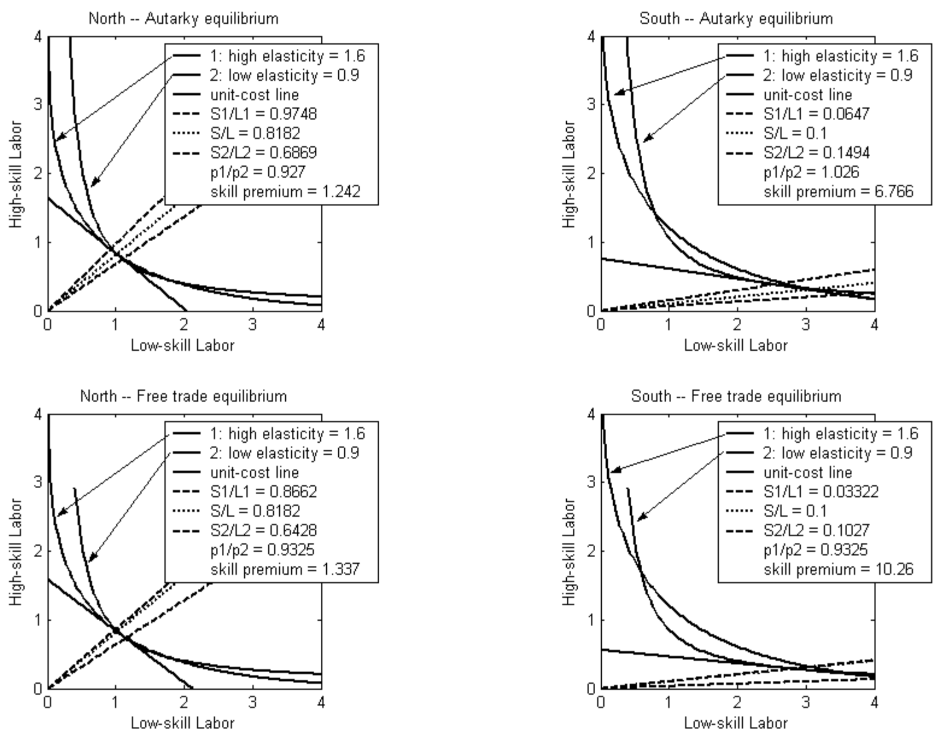

Figure 12: "Globalization"

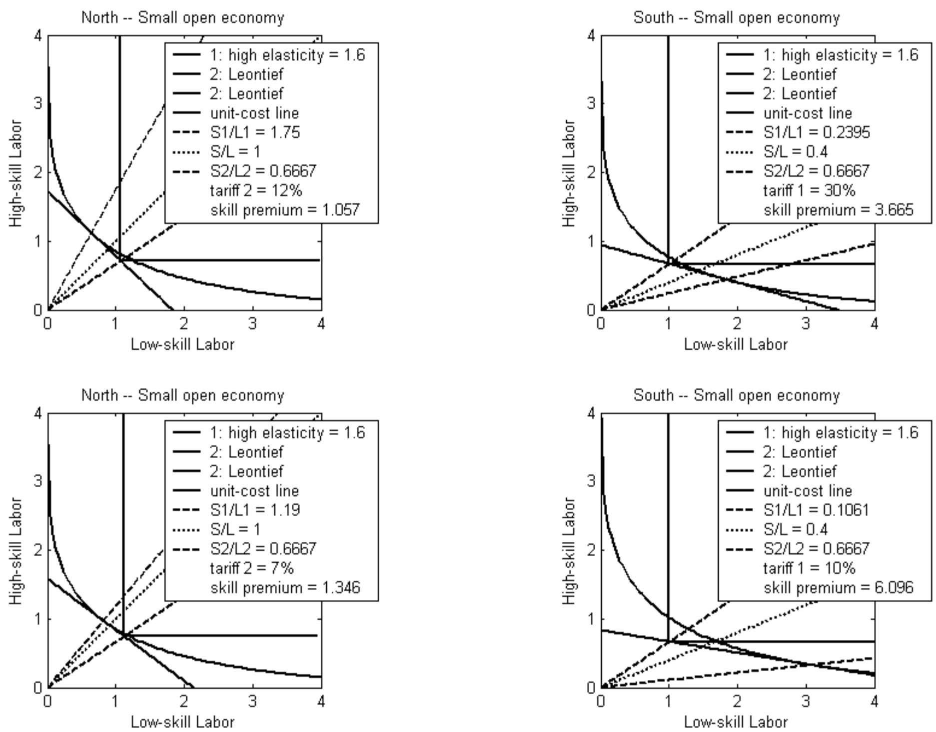

Figure 13: "Tariff Reductions", Leontief

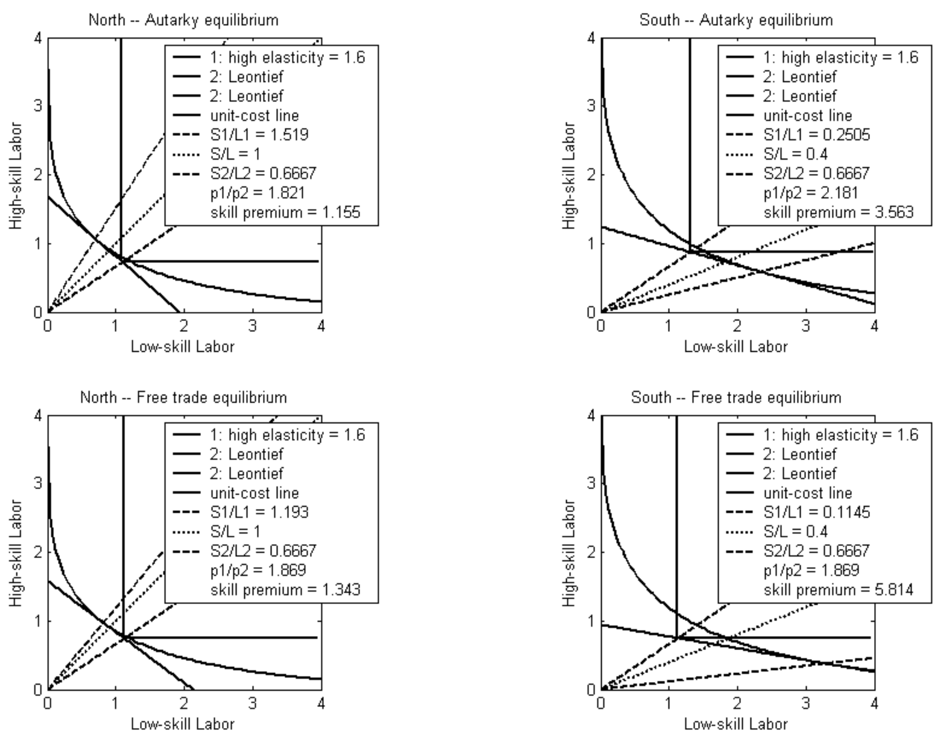

Figure 14: "Globalization", Leontief

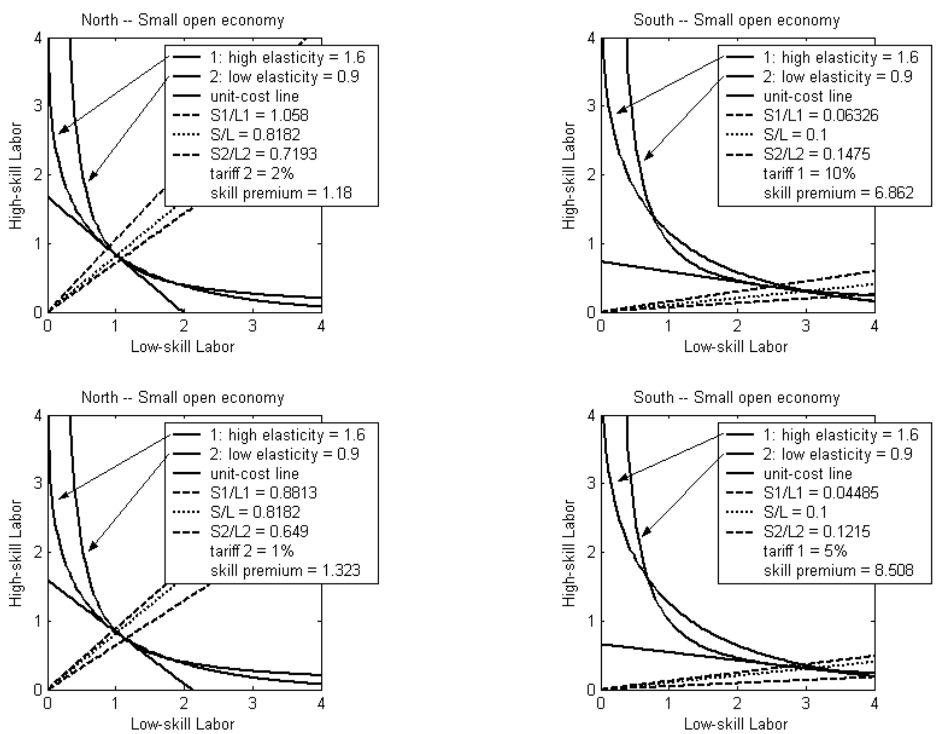

Figure 15: "Tariff Reductions"