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The Skill Bias of World Trade

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Abstract

Under plausible assumptions about preferences and technology, the model in this paper suggests that the entire volume of world trade matters for wage inequality. Therefore, trade integration, even among identical countries, is likely to increase the skill premium. Further, we argue that empirical evidence of a falling relative price of skill-intensive goods can be reconciled with the fast growth of world trade and that the intersectoral mobility of capital exacerbates the effect of trade on inequality. We provide new empirical evidence in support of our results and a quantitative assessment of the skill bias of world trade.

JEL classification: F12, F16.

Keywords: Skill Premium, Scale Effect, Intra-Industry and Inter-Industry Trade.

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1 Introduction

Wage inequality has widened over the last two decades. This fact has stimulated a growing body of research, which has pointed at skill-biased technical change and international trade as major explanations. It has been argued that technology can be at the root of the increase in inequality because recent innovations in the production process, such as the widespread introduction of computers, have boosted the relative productivity of skilled workers.[1] In contrast, trade models generally attribute the rising skill premium in OECD countries to the growing competition with imports from low-wage producers due to globalization.[2] However, the current consensus is that the role of international trade has little empirical relevance compared to the role of technology. There are four main reasons why the conventional trade explanation fails to convince. First, although the last two decades have witnessed a substantial increase in the volume of North-South trade, advanced countries still trade too little with developing countries for the effect of low-price imports to be quantitatively relevant.[3] Second, the rise in the skill premium has also occurred in many developing countries, which runs counter to the conventional trade story.[4] Third, most studies suggest that the relative price of skill-intensive goods did not increase during the period of rising inequality,[5] whereas trade models imply an unambiguous positive relationship between prices of factors and goods. Fourth, the change in relative wages is associated with a substantial increase in the demand for skill within all industries (skill upgrading), whereas the standard explanantion suggests that a trade-induced expansion of skill-intensive industries should be accomodated by skill downgrading.[6]

In this paper, we propose a new role of international trade in explaining wage inequality consistent with the empirical evidence. We do so by revisiting the *new trade theory*'s account of the distributional effects of intra-industry trade. By definition, intra-industry trade is trade

[1] See, among others, Autor, Katz and Krueger (1998).

[2] In particular, Wood (1994, 1998) proposes an augmented Heckscher-Ohlin theory based on specialized trading equilibria.

[3] Wood (1998) reports that imports of manufactures from developing countries constitute a small fraction of OECD GDP (about 3%), although this share has almost tripled between 1980 and 1995. The point that these volumes of trade are too small to have an important effect on wage inequality has been forcefully made by Krugman (2000). Leamer (2000) has criticized this argument, as the connection between trade volumes, their factor content and factor prices is model-specific. Deardorff (2000) and Deardorff and Staiger (1988) study specific cases where the factor content of trade can be used to infer how a move to autarky would have affected factor shares.

[4] For evidence on wage inequality in developing countries see Robbins (1996), Hanson and Harrison (1999) and Berman, Bound and Machin (1998).

[5] In particular, Lawrence and Slaughter (1993) document a decline in the relative price of US skill-intensive goods in the 1980s. See also Slaughter (2000) on this point.

[6] See, in particular, Berman, Bound and Griliches (1994), Berman, Bound and Machin (1998) and Autor, Katz and Krueger (1998).

in goods with similar factor intensities; therefore, according to conventional wisdom, it has no impact on relative factor demand and cannot explain the evolution of the skill premium. We argue that this seemingly plausible result hinges either on Cobb-Douglas preferences or perfect symmetry between sectors. We show that an elasticity of substitution in consumption greater than one and stronger returns to scale in the skill-intensive sectors imply that any increase in the volume of trade, even between identical countries, tends to be skill-biased. The intuition behind this result is very simple. Trade expands the market size of the economy, which is beneficial because of increasing returns. In relative terms, however, output increases by more in the skill-intensive sector, since it is characterized by stronger economies of scale, and the relative price of the skill-intensive good therefore falls. With an elasticity of substitution in consumption greater than one, the demand for skill-intensive goods increases more than proportionally, raising their share of total expenditure and therefore also the relative wage of skilled workers.

This result has important implications. First, it suggests that the entire volume of world trade matters for inequality and not only the small volumes of North-South trade. We show that, under reasonable parameter values, the skill bias of trade integration between two identical countries is quantitatively relevant. Second, if the skill-biased scale effect is strong enough to overcome the standard factor proportions effect, international trade will spur inequality even in the skill-poor developing economies, making the model consistent with the evidence of rising skill-premia in developing countries after trade liberalization. In particular, we show in a simple numeric exercise that trade integration between Mexico and the United States can account for a significant increase in the Mexican skill premium. Third, our model can explain the decline in the relative price of skill-intensive goods during the period of rising skill premia and growing volumes of world trade. In the framework we propose, the so-called price puzzle (the empirical finding that relative factor and good prices moved in opposite directions) simply disappears. Fourth, we show that, so long as our mechanism applies to intermediate goods (or activities) within industries, it can also explain skill-upgrading within all industries.

We also extend our analysis by introducing physical capital. As the capital stock is an important component of economic size, we find that its accumulation tends to increase the skill premium. More interestingly, we show that the intersectoral mobility of capital is likely to magnify the effects of trade integration on wage inequality. Our findings are consistent with both the evidence on capital relocation towards skill-intensive sectors (Caselli, 1999) and the large literature on capital-skill complementarity.

As mentioned, our results rest on returns to scale being stronger in the skill-intensive sectors and the elasticity of substitution between goods of different skill-intensity being greater than one. How realistic are these assumptions? Available estimates of industry-level returns to scale are often shaky due to methodological hurdles. Two recent papers (Antweiler and Trefler, 2002; Morrison and Siegel, 1999) provide evidence of both increasing returns and sectoral asymmetries in returns to scale that strongly support our theory, although their results depend heavily on specific identification assumptions and functional forms. Other influential papers, e.g., Burnside (1996) and Basu and Fernald (1997), find instead no evidence of increasing returns in the typical manufacturing industry.[7] However, independent of the methodology used, the empirical literature finds evidence of sectoral asymmetries in returns to scale. For instance, Burnside (1996) shows that the cross-industry equality restrictions on the parameters capturing returns to scale are always and overwhelmingly rejected. Unfortunately, as recognized by the author himself, his estimates of industry-level returns to scale are little reliable, due to the loss of precision once the cross-industry equality restrictions are removed.[8] We therefore return to Morrison and Siegel (1999) and Antweiler and Trefler (2002) to infer the sectoral pattern of returns to scale.

Morrison and Siegel (1999) estimate returns to scale in US manufacturing industries at the two-digit industry level for the period 1979-1989. Figure 1 plots their estimates against a measure of sectoral skill-intensity. For each industry, the vertical axis reports the output elasticity of the long-run total cost function (an inverse measure of internal and external scale economies) and the horizontal axis the share of production workers in total employment in 1990 (an inverse measure of skill-intensity). The diagram clearly shows a positive correlation between skill-intensity and scale economies. We also report a weighted regression line, whose slope coefficient and standard error are 0.59 and 0.21, respectively.[9] Similar results are reported by Antweiler and Trefler (2002); using international trade data for 71 countries and a very different methodology, they find that skill-intensive sectors, such as Petroleum Refineries

[7] These papers rely on exogenous variation for identifying returns to scale, which can also be problematic in the absence of valid instruments. The main problem is that the instruments generally used in this literature are weakly correlated with the inputs in some industries, which may help explain why industry-level estimates of returns to scale are generally unreliable.

[8] Note that in 3 out of 20 industries Burnside finds that returns to scale are less than zero, which means that increasing inputs reduces output. In one case the parameter is around zero, in another case it is greater than 2 and in one more case it is less than .65. However, after discarding these implausible estimates, the remaining 14, ranging from 0.73 to 1.31, show a positive and significant association with skill-intensity. In particular, the coefficient of a weighted regression (as in Figure 1, below) of the output elasticity of total cost on the share of production workers in total employment equals .721 with a standard error of .376.

[9] In a very recent paper, Diewert and Fox (2004) also provide estimates of sectoral returns to scale in 18 US two-digit SIC industries using different data and methodology. Remarkably, when we run the regression plotted in Figure 1 using their estimates, we find much the same result: the coefficient on the share of non-production workers equals .53, with a standard error of .30.

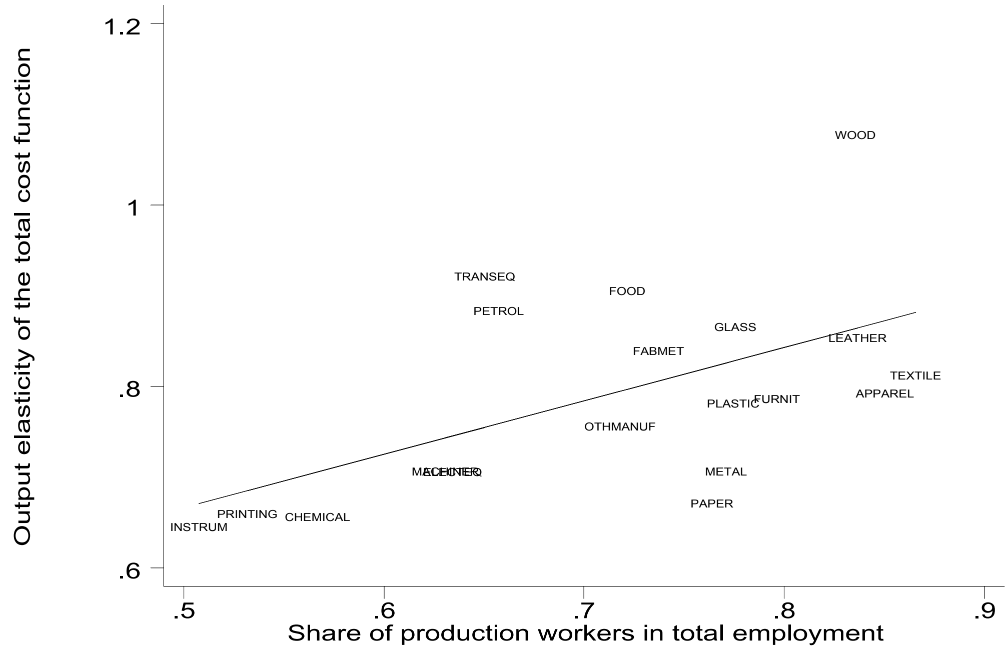

Figure 1: Skill-intensity and increasing returns

and Coal Products, Pharmaceuticals, Electric and Electronic machinery and Non-Electrical Machinery, have an average scale elasticity around 1.2, whereas low skill-intensive sectors, such as Apparel, Leather, Footwear and Food, are characterized by constant returns.[10] Finally, note that many skill-intensive activities (such as R&D and Marketing) have the nature of fixed costs and therefore tend to generate scale economies.

Moving to our second crucial assumption, both direct and indirect evidence suggests that the elasticity of substitution between goods with different skill-intensity (ϵ) is greater than one. In particular, a unit elasticity would imply that expenditure shares are unresponsive to relative price changes, but this is contradicted by US data. To show this, we have first computed the relative expenditure (E_h/E_l) on two aggregates of high and low skill-intensive goods.[11] In the years from 1980 to 2000, we find that the relative expenditure on skill-intensive

[10] More precisely, simple calculations on their results show that manufacturing sectors with strong evidence of increasing returns have an average index of skill-intensity (the normalized ratio of workers who completed high school to those who did not) equal to 0.4 (0.32 when including natural resources), while those with constant returns have an average value of 0.12. The remaining sectors, with non-robust estimates of returns to scale, lie in the intermediate range, with an average skill-intensity of 0.23.

[11] Data is from the OECD Stan Database, whose principal source for the US is the Bureau of Economic Analysis. The aggregate of skill-intensive goods includes: Chemicals and chemical products, Coke, refined petroleum products and nuclear fuel, Machinery and equipment, Transport equipment, and Printing and pub-

goods increased by more than 25%, from 1.04 to 1.3. Then, following a standard practice, we have computed the price index for each aggregate as the average of the price deflators of industries belonging to each group weighted by the employment shares at the beginning of the period.[12] Using 1990 as the base year, we find that the relative price of unskill-intensive goods (P_l/P_h) increased by more than 25%, from 0.93 in 1980 to 1.20 in 2000, a result broadly consistent with most of the studies on product prices surveyed in Slaughter (2000). In Figure 2 we plot the relatioship between expenditure shares and the relative price. The log of the relative expenditure on skill-intensive goods is on the vertical axis, $\log(E_h/E_l)$, and the log of the relative price of unskill-intensive goods is on the horizontal axis, $\log(P_l/P_h)$. Also reported in the figure is a regression line, whose slope coefficient and standard error are 0.44 and 0.08, respectively, with an R-squared of 0.62. Given that the slope coefficient is equal to $\epsilon - 1$, the estimated coefficient implies an elasticity of substitution close to 1.5, consistent with our assumption. When controlling for the log of per capita GDP (taken from the WDI dataset), the coefficient of the relative price is slightly reduced (0.36), but is still significant at the 7%-level (with a standard error of 0.19). In contrast, the per capita GDP coefficient is positive (0.02), as expected, but small and imprecisely estimated (its standard error equals 0.05).

Compelling indirect evidence also indicates that the elasticity of substitution in consumption is significantly greater than one. In particular, in our basic model ϵ coincides with the aggregate elasticity of substitution in production between skilled and unskilled workers.[13] We can then refer to studies that provide estimates of this alterantive parameter. Freeman (1986) concludes his review of the empirical evidence suggesting a value for the elasticity of substitution between more and less educated labor in the range between 1 and 2. Hamermesh and Grant (1979) review 20 estimates of the elasticity of substitution between production and non-production workers and find a mean estimate of 2.3. Further, using a different macroeconomic approach, Krusell et al. (2000) report an estimate of 1.67 for the US economy, while Katz and Murphy (1992) find a value of 1.41.

Having provided evidence in support of the main assumptions, we also confront the model's results with data. We do this in the final part of the paper, where we test for the empirical relevance of skill-biased scale effects. In particular, building on recent work by Alesina,

lishing. The aggregate of unskill-intensive goods includes all the other manufacturing industries. Expenditure on each aggregate is calculated as production plus net imports.

[12] Our results are unchanged when using end of the period employment shares as weights.

[13] This is a special feature of the specific factor model we use. In a more general formulation studied in the Appendix, we show that an aggregate elasticity of substitution in production greater than one also implies an aggregate elasticity in consumption greater than one.

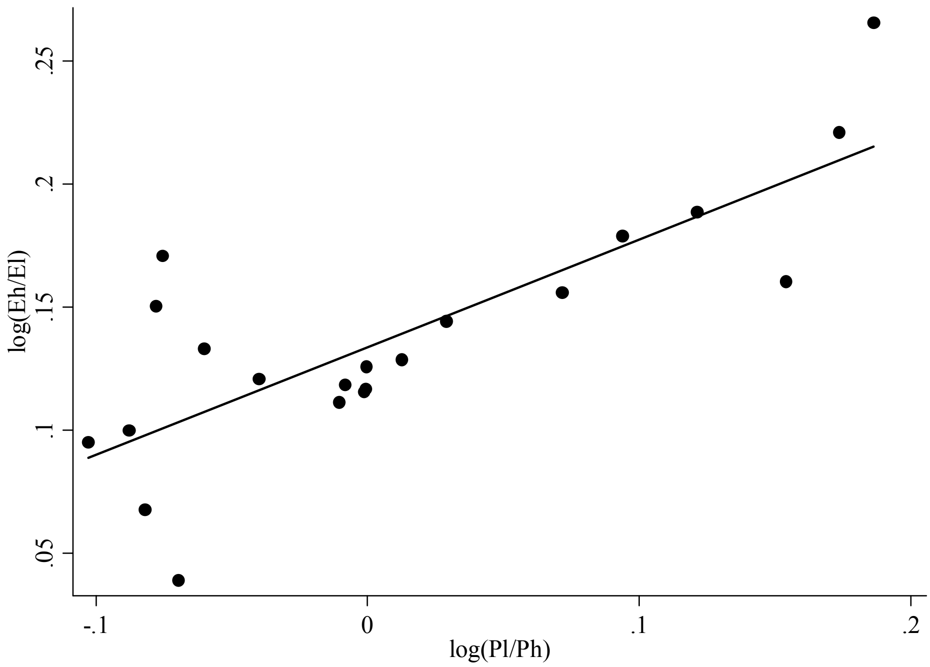

Figure 2: Relative expenditure as a function of the relative price

Spolaore and Wacziarg (2000), we propose various strategies to identify scale effects in two different datasets: a cross-section of economy-wide Mincerian returns to education and a panel of manufacturing skill premia. Our results are broadly consistent across datasets, specifications and estimating methods. They suggest that scale is skill-biased and that the bias is large in magnitude, with an estimated scale elasticity of skill premia often higher than 20%.

We are not alone in reconsidering the role of trade in explaining wage inequality. Neary (2002) and Thoenig and Verdier (2003) develop models where trade liberalization between similar countries can lead to skill-biased technical change. The idea underling their models is that of "defensive innovation": increased competition makes skill-intensive technologies more profitable because they deter the entry of new firms. In contrast, we show that even abstracting from technical change and strategic considerations, the trade-induced expansion in market size is sufficient to raise inequality.[14] Our result is also related to Acemoglu (2003). In his view, North-South trade induces skill-biased technical change by making skill-complement

[14] Another channel through which trade can affect skill premia in models of endogenous technical change is by affecting the reward to innovation, an activity that is likely to be skill-intensive. This mechanism is studied by Dinopoulos and Segerstrom (1999).

innovations more profitable. However, trade between identical countries plays no role and trade opening in a developing country is unlikely to have an effect on the direction of technical change, since no single developing country has the economic size to affect world incentives. Another related work is Dinopoulos et al. (2001). In their model, intra-industry trade expands firm size, which is assumed to be skill-biased, and hence rises the skill premium. In this respect, a fundamental contribution of our approach is to show how an increase in scale leads to skill-biased demand shifts without relying on non-homotheticicities. Further, they consider a one-sector economy only, thereby missing some general equilibrium implications of trade models (e.g., the evolution of relative prices). Manasse and Turrini (2001), instead, show that, in the presence of heterogeneity among skilled workers, trade can spur within-group wage inequality, while we focus on between-group inequality.

Finally, in models of outsourcing (e.g., Feenstra and Hanson, 1996; Zhu and Trefler, 2003) the relocalization of production from OECD countries to developing countries through trade in intermediates increases the demand for skilled labor. This happens because the outsourced activities are unskilled-labor intensive relative to those performed in the developed world, but skilled-labor intensive relative to those performed in the developing countries. Our approach shares the basic insight that trade in intermediate inputs affects both import-competing and input-using sectors; however, outsourcing typically takes place between dissimilar countries, whereas the kind of trade we emphasize is omnipervasive and most relevant for industrial countries. Moreover, in our view the skill bias of world trade is a pure consequence of trade liberalization, whereas in models of outsourcing other aspects of globalization are also crucial, such as international capital flows or technological catching up. In summary, our contribution to this growing literature is to consider a more general mechanism based on asymmetries across activities in returns to scale that is both empirically relevant and able to reconcile several puzzling facts.[15]

The plan of the paper is as follows. Section 2 illustrates the basic model, analyzes the effects of international trade on the skill premium and shows that the intersectoral mobility of physical capital may magnify the skill-biased scale effect. Section 3 reconciles the role of trade in explaining wage inequality with the main stylized facts. Section 4 tests for the empirical relevance of the model using two different datasets. Section 5 concludes.

[15] An alternative approach, taken by Ethier (2002), is to disregard sectoral asymmetries to focus instead on the intra-sectoral substitution between inputs. Ethier shows that trade and technical progress can increase wage inequality provided that skilled labor and equipment are complement and that unskilled labor and outsourcing are substitutes.

2 A Simple Model

2.1 Preferences

Consider a country endowed with H units of skilled workers and L units of unskilled workers, where two final goods are produced. Consumers have identical homotetic preferences, represented by the following CES utility function:

$$U = \left[(Y_l)^{\frac{\epsilon-1}{\epsilon}} + (Y_h)^{\frac{\epsilon-1}{\epsilon}} \right]^{\frac{\epsilon}{\epsilon-1}}, \tag{1}$$

where Y_h and Y_l stand for the consumption of final goods h and l, respectively, and $\epsilon > 1$ is the elasticity of substitution between the two goods. The relative demand for the two goods implied by (1) is:

$$\left(\frac{P_h}{P_l} \right)^{-\epsilon} = \frac{Y_h}{Y_l}, \tag{2}$$

where P_h and P_l are the final prices of goods l and h, respectively. Note that $\epsilon > 1$ implies that a fall in the relative price induces a more than proportional increase in relative demand. This is a crucial assumption for our results.

2.2 Production and Market Structure

Goods h and l are produced by perfectly competitive firms by assembling n_i $(i = l, h)$ own-industry differentiated intermediate goods. In particular, we assume that the production functions for final goods take the following CES form:[16]

$$Y_i = \left[\int_0^{n_i} y_i(v)^{\frac{\sigma_i-1}{\sigma_i}} dv \right]^{\frac{\sigma_i}{\sigma_i-1}}, \tag{3}$$

where $y_i(v)$ is the amount of the intermediate good type v used in the production of good i, and σ_i is the elasticity of substitution among any two varieties of intermediates used in sector i. In the following, we assume that $\sigma_l > \sigma_h > \epsilon$. In words, the elasticity of substitution among intermediates is greater in sector l than in sector h. Further, the elasticity of substitution in production among intermediates used in each sector is greater than the elasticity of substitution in consumption between the final goods.

[16] As discussed later on, these production functions exhibit increasing returns to scale and were introduced into trade theory by Ethier (1982).

The price for final good i (equal to the average cost) implied by (3) is:

$$P_i = \left[\int_0^{n_i} p_i \left(v \right)^{1-\sigma_i} dv \right]^{1/(1-\sigma_i)}, \tag{4}$$

where $p_i(v)$ is the price of the intermediate good type v used in the production of good i.

The two sectors producing intermediates are monopolistically competitive *a là* Dixit-Stiglitz with symmetric firms. The production of each intermediate in sector i involves a fixed requirement, F_i, and a constant marginal requirement, c_i, of labor. In order to keep the algebra as simple as possible, we assume that the two sectors are extreme in terms of skill-intensity, so that sector h uses only skilled workers H, whereas sector l uses only unskilled workers L. In the Appendix, we generalize our results to a setting where both sectors use both types of labor. Hence, the total cost function of a single variety produced in sector i is:

$$TC_i = (F_i + c_i y_i) w_i, \tag{5}$$

where w_h and w_l are the wage rates of skilled and unskilled workers, respectively.

Profit maximization by producers of intermediates in the two sectors implies a markup pricing rule:

$$p_i(v) = p_i = \left(1 - \frac{1}{\sigma_i} \right)^{-1} c_i w_i = w_i, \tag{6}$$

where the latter equality follows from a choice of units such that $c_i = \left(1 - \frac{1}{\sigma_i}\right)$. Hence, we have:

$$\frac{p_h}{p_l} = \omega, \tag{7}$$

where $\omega = w_h / w_l$ is the skill premium. Intuitively, the relative price of any variety of sector h intermediates is an increasing function of the skill premium, since h is skill-intensive relative to l.

A free-entry condition guarantees zero profits in equilibrium:

$$\pi_i(v) = \pi_i = \left(\frac{y_i}{\sigma_i} - F_i \right) w_i = 0$$

and hence

$$y_i = F_i \sigma_i = 1, \tag{8}$$

where the latter equality follows from setting $F_i = 1/\sigma_i$.[17]

[17] This assumption is meant to simplify the algebra only and is innocuous for the purpose of the paper.

Equations (6) and (8) allow us to simplify the expressions for P_i and Y_i:

$$\begin{aligned} Y_i &= n_i^{\frac{\sigma_i}{\sigma_i - 1}} && (9) \\ P_i &= n_i^{\frac{1}{1-\sigma_i}} p_i. && (10) \end{aligned}$$

As equation (9) shows, the elasticity of Y_i with respect to n_i is greater the lower is σ_i. Hence, σ_i can be interpreted as an inverse measure of external scale economies at the industry level.[18] Our assumption $\sigma_l > \sigma_h$ is thus equivalent to assuming stronger increasing returns to scale in sector h than in sector l.[19]

2.3 General Equilibrium

Conditions for full employment of skilled and unskilled workers determine the number of varieties produced in each sector:

$$n_l = L \quad \text{and} \quad n_h = H. \tag{11}$$

Let $\theta = H/\overline{L}$ be the country share of skilled workers in the total workforce, $\overline{L} = H + L$. Equations (11) can then be rewritten as:

$$n_l = (1-\theta)\,\overline{L} \quad \text{and} \quad n_h = \theta \overline{L}. \tag{12}$$

Substituting (9), (10), (7) and (12) into (2), and rearranging gives an equilibrium expression for the skill premium:

$$\left[\theta \overline{L}\right]^{\frac{\sigma_h - \epsilon}{\epsilon(\sigma_h - 1)}} \omega = \left[(1-\theta)\,\overline{L}\right]^{\frac{\sigma_l - \epsilon}{\epsilon(\sigma_l - 1)}}, \tag{13}$$

which is interpreted below.

As argued later on, our normalizations do not affect the *elasticity* of the skill premium to a change of any parameters (they only affect its *level*).

[18] These external scale economies, sometimes called "returns from specialization", come from the benefit of having more varieties in the production function for final goods (see eq. 3), and not directly from the presence of fixed costs at the firm level (as firm size is constant). Returns from specialization depend on σ_i only, and disappear when varieties are perfect substitutes, as in this case only the overall quantity of inputs (and not also their variety) matters for final output.

[19] A production function $Y = f(v)$ exhibits increasing returns to scale if $f(\lambda v) > \lambda f(v)$ for $\lambda > 1$. An index of scale economies is the elasticity of $f(\lambda v)$ with respect to λ: $\frac{\partial f(\lambda v)}{\partial \lambda}\frac{\lambda}{f(\lambda v)} = \frac{\sigma_i}{\sigma_i - 1}$. This index is clearly decreasing in σ_i. Note, also, that returns to scale do not depend on marginal and fixed costs, as firm size is constant. This also means that our normalizations on F_i and c_i affect the level of output but not its scale elasticity. Since our main results depend on the scale elasticity of output, they are unaffected by the normalizations.

2.4 Trade and the Skill Premium

We can now analyze the effects of trade integration on the skill premium. Since we focus on equilibria with factor price equalization (FPE), we can obtain the free trade prices by applying the above results to a hypothetical integrated economy whose endowments are the sum of those of each country. In particular, totally differentiating equation (13) and using the implicit function theorem, we can decompose the change in the skill premium into the following components:

$$\frac{d\omega}{\omega}=\left[\frac{(\epsilon-1)(\sigma_l-\sigma_h)}{\epsilon\,(\sigma_h-1)\,(\sigma_l-1)}\right]\frac{d\overline{L}}{\overline{L}}-\left[\frac{\sigma_h-\epsilon}{\epsilon\,(\sigma_h-1)}+\frac{\sigma_l-\epsilon}{\epsilon\,(\sigma_l-1)}\frac{\theta}{1-\theta}\right]\frac{d\theta}{\theta}. \tag{14}$$

Equation (14) shows how the skill premium is affected by a variation in the size of the economy ($d\overline{L}/\overline{L}$) and the relative scarcity of skilled workers ($d\theta/\theta$). We use equation (14) to first study the effect of intra-industry trade on wage inequality. As shown by Krugman (1979), in a Dixit-Stiglitz framework trade integration among two identical countries is formally equivalent to an increase in country size, $\overline{L}$. Given that $\sigma_l > \sigma_h > \epsilon > 1$, equation (14) implies that the coefficient of $\frac{d\overline{L}}{L}$ is positive, and that its magnitude depends positively on the elasticity of substitution ϵ and the sectoral asymmetries $(\sigma_l-\sigma_h)$ in the degree of returns to scale. Thus, pure intra-industry trade among identical countries, often presumed to have no distributional effects, turns out to be skill-biased.

Equation (14) also shows the effect of inter-industry trade on wage inequality. Integration between dissimilar countries still implies an increase in the overall size of the economy, but also changes the perceived relative scarcity of factors. Since the coefficient of $d\theta/\theta$ is negative, an increase (fall) in the relative supply of skilled labor has the effect of reducing (increasing) the skill premium.[20] This effect works through the well-known mechanics of the Heckscher-Ohlin-Samuelson theorem, and can dampen or magnify the upward pressure on the skill premium due to the market size effect. Moreover, it can lead to a decline in the absolute wage of the factor perceived as more abundant after trade integration, whereas the first effect ($d\overline{L}/\overline{L}$) tends to increase the real wage of all factors.

What drives the skill bias of trade? Growth in the size of the market increases relative productivity in the skill-intensive sector, since it enjoys stronger returns to scale. At the same time, an elasticity of substitution in consumption greater than one ensures that the relative price of skill-intensive goods does not fall too much, so that the market size expansion increases the share of skill-intensive goods in total income and hence the skill premium.

[20] Note that the coefficient of $d\theta/\theta$ is negatively affected by the elasticity of substitution ϵ, as a high substitutability implies a weak price effect of an increase in the relative supply.

2.5 Introducing Physical Capital

We now show how the introduction of physical capital, assumed to be mobile across sectors, magnifies the skill-biased scale effect of trade. With physical capital (K), the total cost function of a single variety produced in sector i becomes:

$$TC_i = (F_i + c_i y_i) r^{\gamma} w_i^{1-\gamma}, \tag{15}$$

where r is the rental rate and γ is the share of capital in sector i's total cost. For simplicity, equation (15) considers the case where capital intensity is the same in both sectors ($\gamma = \gamma_h = \gamma_l$).[21] The relative price of skill-intensive varieties implied by (15) and profit maximization becomes:

$$\frac{p_h}{p_l} = \frac{r^{\gamma} w_h^{1-\gamma}}{r^{\gamma} w_l^{1-\gamma}} = \omega^{1-\gamma}. \tag{16}$$

Equations (2), (9) and (10) are unchanged; together with (16) they imply:

$$n_h^{\frac{\sigma_h - \epsilon}{\epsilon(\sigma_h - 1)}} \omega^{1-\gamma} = n_l^{\frac{\sigma_l - \epsilon}{\epsilon(\sigma_l - 1)}}. \tag{17}$$

Using Shephard's lemma, the demand for each factor can be found from the total cost function (15). Noting that $\frac{\partial}{\partial w_i} r^{\gamma} w_i^{1-\gamma} = (1-\gamma) r^{\gamma} w_i^{-\gamma}$ and $\frac{\partial}{\partial r} r^{\gamma} w_i^{1-\gamma} = \gamma r^{\gamma-1} w_i^{1-\gamma}$, we have that the conditions for full employment of physical capital, skilled and unskilled workers are given by:

$$\begin{aligned} K &= \gamma r^{\gamma-1} w_h^{1-\gamma} n_h (F_h + c_h y_h) + \gamma r^{\gamma-1} w_l^{1-\gamma} n_l (F_l + c_l y_l) \\ H &= (1-\gamma) r^{\gamma} w_h^{-\gamma} n_h (F_h + c_h y_h) \\ L &= (1-\gamma) r^{\gamma} w_l^{-\gamma} n_l (F_l + c_l y_l). \end{aligned} \tag{18}$$

After setting $w_l = 1$, we can use (18) to express n_h and n_l as functions of the skill premium and the exogenous variables:

$$n_h = \frac{H\omega^{\gamma}}{(1-\gamma)^{1-\gamma}} \left(\gamma \frac{L + H\omega}{K}\right)^{-\gamma} \quad \text{and} \quad n_l = \frac{L}{(1-\gamma)^{1-\gamma}} \left(\gamma \frac{L + H\omega}{K}\right)^{-\gamma}. \tag{19}$$

[21] The assumption of equal capital shares in the two sectors simplifies significantly the algebra and seems natural, given that there is no strong evidence of any robust correlation between capital intensity and skill-intensity. In fact, equal capital intensity is also the benchmark case studied by Feenstra and Hanson (1996) in their related work on outsourcing and wage inequality. In any event, we have also analyzed the more general case when the two sectors differ in capital intensity. We report in a following note how relaxing this assumption affects the main results.

Substituting (19) into (17) and solving for ω gives the equilibrium skill premium. Differentiating with respect to ω, K and $\overline{L} = H + L$, and using the implicit function theorem, we find the elasticity of the skill premium to changes in the scale of the economy to be:

$$\frac{d\omega}{\omega} = \frac{\left[\gamma \frac{dK}{K} + (1-\gamma)\frac{d\overline{L}}{\overline{L}}\right] \frac{(\epsilon-1)(\sigma_l-\sigma_h)}{\epsilon(\sigma_h-1)(\sigma_l-1)}}{1-\gamma\left[\frac{\epsilon-1}{\epsilon}\frac{1}{1-\theta+\theta\omega}\left(\frac{\sigma_h(1-\theta)}{\sigma_h-1}+\frac{\sigma_l\theta\omega}{\sigma_l-1}\right)\right]}, \tag{20}$$

where again $\theta = H/\overline{L}$ is the share of skilled workers in the total labor force.[22] Note that the coefficient multiplying the scale variables in the square bracket of the numerator is equal to the scale elasticity in (14). But now the denominator in (20) is less than one and decreasing in γ.[23] Therefore, the effect on the skill premium of trade integration among two identical countries, i.e., a doubling of both K and $\overline{L}$, is now greater the larger is the share γ of capital in total cost.[24] Further, equation (20) shows that capital accumulation and capital inflows tend to increase the skill premium, as they contribute to expand the scale of the economy. This result is consistent with the literature documenting capital-skill complementarities (see Krusell et al. 2000, among others). To see why capital magnifies the effects of trade integration on the skill premium, it is instructive to study the change in the allocation of capital between the two sectors:[25]

$$\frac{K_h/n_h}{K_l/n_l} = \omega^{1-\gamma}. \tag{21}$$

Equation (21) shows that the trade-induced rise in the skill premium is associated with a relative increase in capital intensity of firms operating in sector h. The reason is that, by expanding market size, trade integration increases the relative productivity of the resources used in the sector enjoying stronger returns to scale. Hence, trade implies an increase in the relative marginal productivity of capital in sector h. Since in equilibrium the rental rate must be equalized across sectors, the only way of restoring the equality after trade integration is by shifting capital out of the less skill-intensive sector and into the skill-intensive sector. As a consequence, the endowment of capital per worker rises for the skilled and falls for the

[22] The elasticity to a change in the relative skill-endowment θ is here omitted, though straightforward to calculate, because we are interested in showing how capital reallocation affects the scale effect.

[23] Note that, assuming decreasing marginal returns to capital in both sectors, we have $\gamma\frac{\sigma_i}{\sigma_i-1} < 1$ for $i = h, l$. This ensures that the denominator of (20) is positive.

[24] In the general case when the capital-intensity is allowed to differ across sectors, we find that an equi-proportional increase in the overall scale of the economy (H, L and K) is more skill-biased when the skill-intensive sector is also capital intensive. Further, an increase in capital only is more beneficial for the factor used in the capital-intensive sector, while an equi-proportional increase in H and L, by raising the price of capital, hurts more the factor used in the capital-intensive sector.

[25] To obtain (21), note that $K_i r = \gamma P_i Y_i$ then use (9), (10) and (16).

unskilled, which further increases wage inequality. Capital reallocations toward skill-intensive sectors introduce the possibility that the real wage of unskilled workers may actually fall with trade integration between identical countries. This is an interesting possibility, since empirical studies suggest that the real wage of less skilled workers may have declined in the US.[26] Note, however, that also the standard Stolper-Samuelson effect (due to trade integration with less developed countries) may have contributed to this fact.

A similar mechanism is at work in Caselli (1999), where a skill-biased technological revolution induces a reallocation of capital toward the skill-intensive sectors. He also provides evidence of a substantial increase in the US sectoral dispersion of capital intensities since the mid-seventies. In particular, Caselli documents capital flows to skill-intensive industries during the period of rising wage inequality. Our contribution is to show that such a reallocation of capital can also be due to trade integration. Therefore, capital mobility magnifies the effects of trade integration on the skill premium and strengthens the quantitative relevance of our analysis.

3 Trade and Wages: Reconsidering the Facts

In this section, we show how our model can reconcile an important role of trade in explaining the rising skill premia with the main stylized facts. The first critique to traditional trade-based explanations concerns their quantitative relevance: North-South trade flows simply do not seem to be large enough to significantly affect wage premia.[27] Compared to the standard Heckscher-Ohlin approach, our model is less exposed to this criticism as it shows that the entire volume of world trade matters for inequality and not only its net factor content. It remains to argue that the trade-induced skill-biased scale effect might be of significant magnitude. To do so, we compute the scale elasticity of the skill premium given by equation (20). A conventional value for the capital share, γ, is 1/3. In the model we use, the elasticity of substitution between goods of different skill-intensity, ϵ, is the same as the elasticity of substitution between skilled and unskilled workers. Estimates of the latter elasticity are mostly in the range (1 - 2), and therefore $\epsilon = 1.5$ is a reasonable benchmark. This value is also consistent with our estimate of

[26] Such a fall seems confined to the period 1980-1995 and affects mostly male workers at the bottom of the wage distribution. Quantifying it poses potentially serious problems arising from the difficulty in measuring the increase in product quality and the value of new goods. Furthermore, during the past decades there has been a large increase in non-wage compensations that are often not accounted for in computing real earnings. See Katz and Author (1999), and references therein, for evidence and discussion.

[27] Leamer (2000) warns that low volumes of trade are compatible with external product markets that dictate lower wages for unskilled workers, because the relationship between the factor content of trade and factor prices is model specific. In fact, our model is an example of a situation in which trade can affect factor prices even when the net factor content of trade is zero (e.g., in case of trade integration between identical countries).

the elasticity of substitution between goods reported in the Introduction. As for industry-level returns to scale, recall that in our model they equal $\sigma_i/(\sigma_i - 1)$. As mentioned, many studies find no significant departure from constant returns to scale in the unskill-intensive sectors, whereas estimates of returns to scale in the skill-intensive sectors vary across studies. We therefore set $\sigma_l/(\sigma_l - 1) = 1$ and let $\sigma_h/(\sigma_h - 1)$ vary. Figure 3 shows the scale elasticity of the skill premium (on the vertical axis) as a function of $\sigma_h/(\sigma_h - 1)$ (on the horizontal axis) for some critical values of ϵ. It can be used to perform some interesting experiments.[28] For instance, with average returns to scale equal to 1.2 ($\sigma_h = 6$) in the skill-intensive sectors (as in Antweiler and Trefler, 2002), the graph shows that the scale elasticity of the skill premium ranges from zero (for $\epsilon = 1$) to 13% (for $\epsilon = 2$), with a value around 8% for $\epsilon = 1.5$. Hence, for plausible parameterizations, the model suggests that trade integration between two identical countries would increase the skill premium by roughly 10%. With less conservative estimates, the scale elasticity of the skill premium would grow very large. For instance, with average returns to scale equal to 1.4 ($\sigma_h = 3.5$) in the skill-intensive sectors (as in Morrison and Siegel, 1999), the scale elasticity of the skill premium would rise over 20% even with an elasticity of substitution less than two.[29] In contrast, with returns to scale equal to 1.1 ($\sigma_h = 11$), consistent with some estimates in Basu and Fernald (1997), the scale elasticity of the skill premium would be below 6% (unless we believe in more extreme estimates for ϵ).

More generally, our simple quantification shows that modest asymmetries in sectoral returns to scale may produce a significant effect of market size on wage inequality, thereby suggesting that empirical studies focusing on North-South trade might be missing an important mechanism through which globalization enhances skill premia. Our empirical analysis, in the next section, will confirm this intuition.

A second observation, seemingly at odds with trade models, is that commercial liberalizations in developing countries seem to be followed by increases in wage premia (e.g., Hanson and Harrison, 1999 and Robbins, 1996). Our model can rationalize this fact if the skill-biased scale effect is strong enough to overcome the factor proportions effect in skill-scarce countries. To see whether this is more than just a theoretical possibility, we use our model to study the episode of trade integration between Mexico and the United States. This case is of particular interest because, prior to 1985, Mexico could be considered a closed economy due to heavy policies of trade protection. In 1985, Mexico announced its decision to join the GATT

[28] Note from equation (20) that $d\omega/\omega$ also depends on θ and ω. Numerical simulations show their effect to be negligible. To draw Figure 3, we have used values of 0.35 and 1.4, respectively.

[29] Note, however, that Morrison and Siegel (1999) estimate positive, but much smaller, increasing returns even in less skill-intensive sectors. Taking this into account would lower the scale elasticity of the skill premium computed in Figure 3.

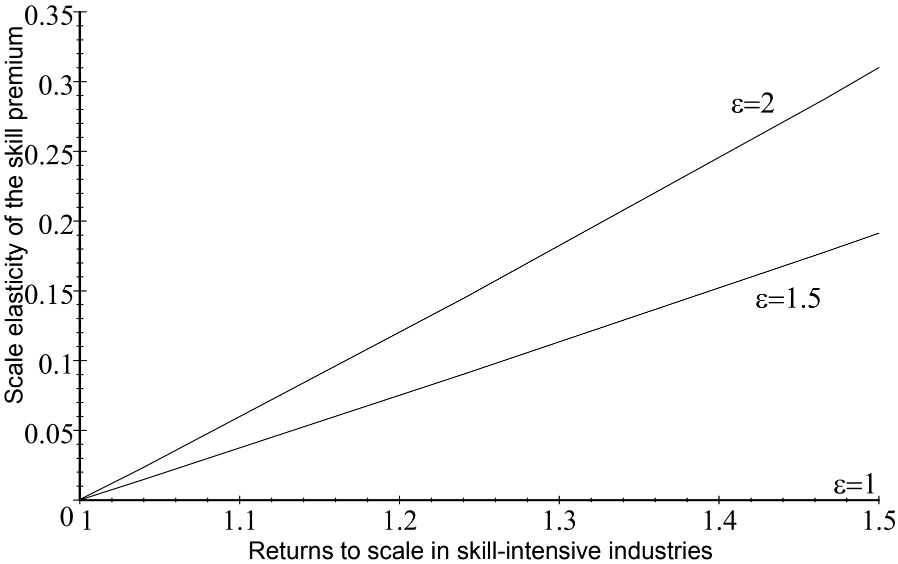

Figure 3: Scale elasticity of the skill premium

and undertook major reforms leading to a reduction in tariffs by 45% and import licenses by more than 75% within three years. During the same period, the skill premium, starting from a value of 1.84, rose by at least 17%. The Mexico experience is also interesting because its major trade partner is the skill-abundant United States. We then perform the following thought experiment. Assume that Mexico was in autarky in 1985; what does our model say about the effect of a complete and instantaneous trade integration with the United States? Using data[30] for the manufacturing sector and the share of white-collar workers as a measure of skilled labor, we have that a move from autarky to the integrated equilibrium implies for Mexico a 4.8 fold increase in the total labor force, a 10.1 fold increase in the aggregate capital stock and a 28.4% increase in the share of white-collar workers. Using these numbers together with the above mentioned parameter values ($\gamma = 1/3$, $\epsilon = 1.5$, $\sigma_h = 6$, $\sigma_l = \infty$), our model predicts the following change in the Mexican skill premium:

$$\frac{d\omega}{\omega} = +0.49 - 0.27 = 0.22$$

where the first number represents the positive scale effect and the second number the neg-

[30] Berman, Bound and Griliches (1994) provide the share of US white-collar workers. The equivalent share for Mexico is reported in Hanson and Harrison (1999). The labor force in manufacturing is taken from the World Development Indicators. The total capital stock is computed from the Penn World Tables.

ative factor proportions effect. Overall, trade opening in skill-scarce Mexico can lead to a considerable 22% increase in the skill premium. These simple calculations suggest that the market size effect can play a significant role in developing countries that experience drastic trade liberalizations.

The third puzzling fact that a satisfactory model should explain is the evolution of relative prices. Though the empirical findings are sometimes mixed, they tend to suggest a *decline* in the relative price of skill-intensive goods during the period of rising skill premia. Our model can help understand this evidence, as it breaks the simple positive relation between the price of goods and factors implied by the standard trade theory. On the one hand, a trade-induced expansion in market size lowers the relative final price of the skill-intensive good:

$$\frac{P_h}{P_l} = \left[\frac{n_l^{\frac{\sigma_l}{\sigma_l - 1}}}{n_h^{\frac{\sigma_h}{\sigma_h - 1}}} \right]^{1/\epsilon}.$$

Our assumption $\sigma_l > \sigma_h$ implies that a larger market is associated with a lower relative price of the skill-intensive final good: as the skill-intensive sector is characterized by stronger returns to scale, its output grows more after an increase in market size and this depresses its relative price. On the other hand, trade increases the relative price of each variety of intermediates in the skill-intensive sector, together with the skill premium, because of the stronger productivity gain:

$$\frac{p_h}{p_l} = \omega^{1-\gamma}.$$

These contrasting implications concerning the effects of international trade on price indexes and prices of individual goods may shed light on the mixed results emerging from empirical studies using different methodologies and different levels of sectoral aggregation. In particular, it is suggestive that Lawrence and Slaughter (1993) show a decline in the relative price of skill-intensive goods using a high level of aggregation, whereas Krueger (1997) finds the opposite result using highly disaggregated data.

A final argument often used to discredit the role of trade is that the demand for skill increased within all industries. We close this section by showing how our theory can also account for this stylized fact. All we need is to interpret the simple model of Section 2 as describing a single industry and to add an upward sloping supply curve of skilled labor. More precisely, assume that in the economy there are two industries producing final consumption goods, X and Y, using industry-specific intermediates of different skill intensity according to the following CES functions:[31]

$$\begin{aligned} X &= \left[(1-\alpha_x)(X_l)^{\frac{\epsilon-1}{\epsilon}} + \alpha_x (X_h)^{\frac{\epsilon-1}{\epsilon}}\right]^{\frac{\epsilon}{\epsilon-1}} \\ Y &= \left[(1-\alpha_y)(Y_l)^{\frac{\epsilon-1}{\epsilon}} + \alpha_y (Y_h)^{\frac{\epsilon-1}{\epsilon}}\right]^{\frac{\epsilon}{\epsilon-1}}, \end{aligned}$$

The production functions for X_l and X_h are identical to those for Y_l and Y_h, that are still given by (3). Thus, returns to scale are higher for intermediates X_h and Y_h (employing skilled workers only) than for intermetiates X_l and Y_l (employing unskilled workers only). The only difference between the two industries X and Y lies in the parameters α_y and α_x, capturing the relative importance of skill-intensive intermediates. Note that this formulation preserves entirely our basic insight: that skill intensive activities (even within industries or plants) are characterized by stronger returns to scale. Under these assumptions, the wage bill share of skilled workers in industry X is given by:

$$\omega \frac{H_x}{L_x} = \frac{\alpha_x}{1-\alpha_x}\left(\frac{X_h}{X_l}\right)^{(\epsilon-1)/\epsilon} \tag{22}$$

where H_x and L_x represent employment in industry X of skilled and unskilled workers, respectively. An analogous expression holds for industry Y. Imposing wage equalization across industries, full employment, and using the reduced forms for X_h and X_l, we can derive an expression that links the labor endowment of the economy to employment in industry X:

$$\left[\frac{L_x}{L-L_x}\right]^{\frac{\sigma_l-\epsilon}{\epsilon(\sigma_l-1)}} = \frac{\alpha_y(1-\alpha_x)}{(1-\alpha_y)\alpha_x}\left[\frac{H_x}{H-H_x}\right]^{\frac{\sigma_h-\epsilon}{\epsilon(\sigma_h-1)}} \tag{23}$$

Note that any increase in H and L must be matched by a proportional increase in H_x and L_x. The same happens in industry Y. Then, if the supply of skill is upward sloping, any increase in the skill premium (due to, say, a market size expansion) will raise H relative to L and, as a consequence of (23), every industry will employ a higher share of skilled workers. The intuition for this result (see eq. 22) is again that, as long as the activities performed by skilled workers enjoy stronger returns to scale than those performed by the unskilled, and the elasticity of substitution among them is sufficiently high, any increase in market size raises the relative demand for skill, even within industries or plants.[32]

[31] Note that ϵ is now to be interpreted as the elasticity of substitution in production between inputs produced with different skill-intensity.

[32] Note that our result is also in line with a general principle emphasized by Feenstra (2004), namely, that trade in intermediate inputs can have an important impact on the structure of production and demand for labor within industries.

4 Empirical Evidence

4.1 Wage Inequality across Countries

We now confront our theory with data on wage inequality across countries. Our model suggests that the skill premium is increasing in market size (the scale effect) and decreasing in the share of skilled workers in total labor force (the factor proportions effect). But what is the concept of market size that matters? In our model it does not simply coincide with the domestic economic size, as it is also influenced by a country's trade regime and the size of the world market: for instance, a large but closed economy can have a smaller market than a small but very open economy. Therefore, the two main ingredients of a country's overall market size are its economic size and trade openness.[33] In the following, we exploit this fact to test the empirical relevance of scale effects for wage inequality. In particular, we build on recent work by Alesina, Spolaore and Wacziarg (2000; henceforth, ASW). These authors have a similar problem of defining country size in order to test for the relevance of scale effects, the main difference being that their concern is with the effects of scale on per capita income, whereas our focus is on skill-biased scale effects. ASW build their empirics on a synthetic scale variable, derived from their theoretical model, which we call *adjusted country size*, $\overline{L}_i^{Adj}$, to recall that it is a measure of country size adjusted for trade openness. This variable is defined as

$$\overline{L}_i^{Adj} = (1 - Op_i)\overline{L}_i + Op_i\overline{L}_w, \tag{24}$$

and is a weighted average of domestic $\left(\overline{L}_i\right)$ and world $\left(\overline{L}_w\right)$ size, where the weight is proxied by a country's trade openness (Op_i). ASW emphasize the following properties of this variable: 1) it rises with the domestic country size; 2) it rises with a country's openness; 3) the effect of country size on $\overline{L}_i^{Adj}$ is lower the higher is a country's openness or, equivalently, the effect of openness is lower the larger is a country.[34] To capture these features of $\overline{L}_i^{Adj}$, ASW use as proxies for overall market size the following three variables: country size (GDP or population), openness and the interaction term between country size and openness, whose expected sign is negative in the presence of a positive scale effect, by virtue of property 3).

Below, we follow ASW's empirical strategy. However, our empirical exercise poses some additional problems with respect to ASW's exercise. The most relevant is that the sample of countries for which we can collect data on wage inequality is at best roughly one half of the

[33] Note, also, that country size and trade openness are inversely correlated, since small countries are generally more open than large countries.

[34] More formally, $\frac{\partial^2 \overline{L}_i^{Adj}}{\partial Op_i \partial \overline{L}_i} < 0$.

sample used by ASW to study scale and per capita income. In our case, a more parsimonious specification of the scale effect is therefore called for. The way we address this problem is straightforward: we simply stick to equation (24) as our main proxy for scale. To compute this proxy, we only need an operational definition of foreign size $\left(\overline{L}_f = \overline{L}_w - \overline{L}_i\right)$. Here, we follow the empirical trade literature. As argued by Harrigan (2000), the relevant world market is composed by that part of countries' endowments "which is engaged in producing goods that are traded internationally". Hence, we define foreign size as the sum of the economic sizes of all foreign countries multiplied by their openness:

$$\overline{L}_f = \overline{L}_w - \overline{L}_i = \sum_{j \neq i}^{N} Op_j \overline{L}_j, \tag{25}$$

where $j = 1, ..N$ are countries in the world, $\overline{L}_j$ is country j's total labor force (or GDP) and Op_j is its openness. $\overline{L}_f$ can be thought of as a proxy for the amount of foreign resources engaged in international markets. Using (25) into (24) and rearranging terms gives our operational definition of country i's adjusted size:

$$\overline{L}_i^{Adj} = \overline{L}_i + Op_i \sum_{j \neq i}^{N} Op_j \overline{L}_j. \tag{26}$$

This scale variable implies that a country's overall size rises due to a greater domestic and foreign exposure to international trade or to a rise in domestic and foreign economic size. For these reasons, $\overline{L}_i^{Adj}$ is close in spirit to the scale variable $\overline{L}_i$ in our model, since the latter captures, in a stylized way, the scale effect induced by variation in both country size and trade integration.[35]

An additional problem posed by our empirics is that data on wage inequality across countries are generally low quality. To address this problem, we confront our theory with data coming from two completely different sources. In this respect, if we can show that our main results are consistent across datasets, we may also conclude that this is not merely by chance. In particular, we exploit the following, widely used sources of cross-country data on wage inequality (ω_{it}) (see the Data Appendix for more details on the datasets and the construction of the variables):

a) Banerjee and Duflo (2004), which updates and completes the dataset in Psacharopoulos (2002), providing data on a cross-section of economy-wide Mincerian returns to education.[36]

[35] More in general, this is a feature of the models ascribed to the so-called new trade theory.

[36] Mincerian returns to education are obtained as the coefficient of years of schooling in a regression of

This cross-section comes itself from different sources and spans the years from the early seventies to the late nineties. Our sample comprises 71 countries at various stages of economic development, from Ethiopia to the US.

b) The U.N.- General Industrial Statistics database, that allows to collect a panel of skill premia between 1970 and 1990. Following other studies, we compute the skill premium as the ratio of nonproduction to production (operatives) wages in total manufacturing. Our sample comprises 44 countries, each observed for at least two (sufficiently distant) years between 1970 and 1990. The average real per capita GDP in the sample equals roughly 40% of the US value in 1990. In the same year, average (current) openness and labor force equal 60% and 21.5 million workers, respectively. There are 35 countries in common between the two datasets.

We focus on specifications of the form:

$$\omega_{it} = \alpha_0 + \alpha_1 Scale_{it} + \alpha_2 \theta_{it} + \alpha_3' X_{it} + d_t + (\eta_i) + \varepsilon_{it},$$

where i and t index countries and time, respectively, d_t and η_i are time and country specific effects (the latter to be included only when using panel data), X_{it} is a vector of controls and ε_{it} is a random disturbance. Our theory of skill-biased scale effects should show up in a positive and significant coefficient α_1.

As proxies for scale we use both *adjusted country size*, $\overline{L}_{it}^{Adj}$, and the three joint proxies used by ASW, namely, *country size*, *openness* and *country size*openness*. In turn, a country's economic size ($\overline{L}_i$) is proxied by both labor force and GDP. Openness is measured both at current prices (*openc*) and at constant prices (*openk*).

Note that, in order for $\overline{L}_{it}^{Adj}$ to make sense, openness must lie in the range $[0, 1]$. Therefore, in computing $\overline{L}_{it}^{Adj}$, we define openness as $((imports + exports)/2)/GDP$. This definition is also more consistent with the definition of foreign size given earlier on. In a couple of instances, even with this normalization, openness is still greater than one. In these cases, we set it equal to one.[37] Finally, to compute $\overline{L}_f$ we have considered all the countries in the world (about 100 countries) with available data on labor force (or GDP) and openness over the period of analysis. Data on openness, labor force and GDP come from the Penn World Tables (Marks 5.6 and 6.1). The simple correlations in two samples between $\overline{L}_{it}^{Adj}$ and labor force ($\overline{L}_{it}$) are 0.77 and 0.51, respectively, whereas the correlations between $\overline{L}_{it}^{Adj}$ and current openness are 0.38 and 0.54.

As proxies for the skill endowment, θ_{it}, we use average years of schooling in the labor force

log(wages) on log(years of schooling). See Banerjee and Duflo (2004), and Psacharopoulos (2002).

[37] The two exceptions are Singapore (1995) in the cross-section of Mincerian returns to education and Luxembourg (1990) in the panel of skill premia.

(ays) and the share of labor force with secondary education (sec). The main source of data on education is the Barro-Lee dataset.

We also control for other potentially relevant determinants of the wage structure. First, in the presence of complementarities among inputs (e.g., capital-skill complementarity), omission of factor endowments may lead to biased results. Therefore, we control for the capital/labor ratio (K/L) and the land/labor ratio (T/L). The series on capital stock are computed using the perpetual inventory method, as in Hall and Jones (1999). Data on land area comes instead from the World Development Indicators (WDI). Moreover, since some theories (e.g., Dinopoulos and Segerstrom 1999; Richardson, 1995) emphasize that investment is a skill-intensive activity and hence that wage inequality may rise with investment, we also control for the *investment share of GDP* (*ki*, from the PWT).

Second, skill-biased technical change may be the true driving force behind the recent increase in wage inequality. To control for the effects of technology on the wage structure, we compute the total factor productivity (TFP) for each country in the sample and for each time period. In this, we again follow Hall and Jones (1999).

Third, we control for real per capita GDP and its square, i.e., for a Kuznets-type relation between income and inequality. The inclusion of per capita GDP is also intended to capture the effect of omitted or mismeasured variables correlated with per capita income (e.g., education, technology, etc.).

Finally, to avoid spurious results due to correlation of our scale variables with time, we control for time specific effects. Interestingly, our results are strengthened by the inclusion of time dummies, which suggests that they are not likely to be driven by the correlation of scale variables with omitted trended variables.

4.1.1 Scale and Mincerian Returns to Education: Results

We start by confronting our theory with a cross-section of Mincerian returns to education. Tables 1-3 summarize the main results. Estimation is by OLS with White-robust standard errors in parethesis. We always control for time specific effects. In Table 1, scale is proxied by adjusted country size. All variables are in logs. To compute $\overline{L}_i^{Adj}$, openness (Op_i, Op_j) is proxied by $openc/2$, whereas economic size ($\overline{L}_i, \overline{L}_j$) is proxied by labor force in eqs. (1)-(4) and by GDP in eqs. (1')-(4'). Note that the simple correlation between these two measures of $\overline{L}_i^{Adj}$ is relatively low (.58), which makes therefore interesting to test for both. Finally, θ_i is proxied by average years of schooling (ays). The main messages conveyed by Table 1 are the following. First, independent of the proxy for economic size and of the specification of the regression equation, the coefficient of the scale variable is generally significant and quite large in magnitude (over 20%). Second, adding controls to the baseline specification generally raises both the size and statistical significance of the scale effect. Third, GDP does generally better than labor force, probably because it is a more comprehensive measure of economic size.

As for the coefficient of the skill endowment, it is never significant and in one case is wrong signed. This is a disappointing result, but not a new one, as it is discussed also in Banerjee and Duflo (2004).[38] As for the controls, in eqs. (2) we add the factor ratios (K/L and T/L) and TFP. Surprisingly, only the coefficient of the land/labor ratio is positive and significant. In particular, the coefficient of TFP is insignificant and (persistently) wrong signed.[39] Since also the capital/labor ratio performs poorly, in eqs. (3) we replace it with the investment share of GDP. Yet, its coefficient is still insignificant and wrong signed. In eqs. (4) we add a second-degree polynomial in per capita GDP to control for a Kuznetz-type relation between income and inequality: in this case, the R-squared doubles and both coefficients have the expected sign, but they are generally insignificant.

In Table 2 we perform some robustness checks. Cross-section regression estimates are generally vulnerable to outliers. In this respect, Figure 4 provides a graphical representation of the partial relation between Mincerian returns to education and $\overline{L}_i^{Adj}$. The vertical axis reports the value of the log rate of return to education after partialling out the estimated effect of the other variables (time dummies included) in specification corresponding to eq. (4'). The plot suggests that the US and Singapore may have a disproportionate influence on the result. Therefore, we rerun eqs. (4) of Table 1 after dropping these two observations. The results are reported in columns (1) of Table 2. Note that the size and significance of the scale effect are little affected: in particular, in eq. (1') the coefficient of $\overline{L}_i^{Adj}$ is still significant at the 1% level.[40]

Since average years of schooling does poorly as a proxy for skill endowment, in eqs. (2) we replace it with the share of labor force with secondary education (*sec*). Note that, while the coefficient of education is still insignificant, the size and significance of the scale effect are further increased: the coefficient of $\overline{L}_i^{Adj}$ is now in both cases larger than 40% and significant at the 1% level.

In eqs. (3) we compute $\overline{L}_i^{Adj}$ by using openness at constant prices (*openk*) instead of

[38] The statistical significance (with the expected sign) of the coefficient of skill endowment is partly vindicated in the second part of the empirical analysis, where we use the skill premium as our dependent variable.

[39] Some experimentation suggests that the significance of our controls is often killed by the inclusion of time dummies. This is not surprising, since most of them are correlated with time.

[40] When dropping also Mexico from the sample, the pattern of coefficients is unaffected; moreover, the coefficient of the scale variable is still sgnificant at the 1% level in eq. (1'), whereas it is significant at the 12% level in eq. (1).

openness at current prices. The correlation between the two measures of $\overline{L}_i^{Adj}$ is very high (.98), and therefore we expect similar results. Indeed they are, as one can see by comparing eqs. (3) in Table 2 with eqs. (4) in Table 1. Finally, in eqs. (4) we add continent dummies to our favorite specification to see whether controlling for continent-specific effects can change the main results. Despite the further loss of degrees of freedom, the precision of our estimates is unaffected.[41]

In Table 3 we run ASW-like regressions. In particular, we proxy for scale with country size, openness and an interaction term between openness and country size. Eqs. (1) show the results for a baseline specification without controls (except for time dummies). In eqs. (1) and (1') we use *ays* as a proxy for skill endowment. Note that the coefficients of the three joint proxies of scale have the expected sign, but only country size is significant at the 10% level. Remarkably, replacing *ays* with *sec* as a proxy for skill endowment, the three coefficients of interest become significant at the 1% level and their size roughly doubles. This is shown in column (1"). It is also interesting that this is the only specification (with this dataset) in which the coefficient of skill endowment turns out significant. It therefore deserves further exploration. In Figures 5 and 6 we show the partial regression plots drawn from eq. (1") relative to GDP and openness, respectively. Figure 5 suggests that the partial relation between wage inequality and GDP is not likely to be driven by outliers. In contrast, Figure 6 shows the presence of two extreme outliers, Singapore and Hong Kong (two very open countries). Note, however, that these observations just lie on the regression line, and hence are not likely to bear a disproportionate impact on the coefficient of openness. In fact, by rerunning eq. (1") after dropping Hong Kong and Singapore, we find much the same results. This is shown in column (1"'). Note, also, that the coefficient of education is now significant at the 5% level. Figure 7, which reproduces Figure 6 in the absence of the two outliers, confirms that the partial relation between the two variables is very strong.

In eqs. (2)-(4) we perform some further robustness checks. In eqs (2) and (3) we add all the controls and use *ays* and *sec*, respectively, as proxies for education. In eqs. (4) we use *ays* and constant openness instead of current openness. The main message from these regressions is that adding controls strengthens the size and significance of the scale effect: now, independent of the proxies used, the coefficients of interest are generally large and highly significant.[42]

[41] As for the coefficients of control variables, the main differences between Tables 1 and 2 are that in the latter the Kuznetz polynomial is often significant, whereas the land/labor ratio is generally insignificant.

[42] For parsimony, we do not report the results of other potentially interesting experiments complementing the results reported in Tables 1 to 3. In particular, we have tried with an interaction term between openness and education, whose expected sign is positive by virtue of the Stolper-Samuelson effect. While leaving generally unaffected the scale effect, the interaction term is hardly significant across specifications and often wrong signed.

4.1.2 Scale and Skill Premia: Results

Next, we confront our theory with a panel of manufacturing skill premia observed around the years 1970, 1980 and 1990. Following a standard practice in empirical studies using panel data, we run regressions both by random-effects and by least squares dummy-variables (LSDV). The former estimator is potentially more efficient, since it exploits all variation in the data, but brings about the risk of biased estimates due to omitted variables; the latter minimizes this risk, although at the cost of a lower efficiency, since it exploits only temporal variation in the data. Consistent with these features of the estimators, we obtain lower standard errors when we use the random-effects estimator. However, regression coefficients are generally similar across estimation methods, which suggests that the potential bias due to omitted variables is not too serious in our case.[43]

The main results are reported in Tables 4-6. Table 4 shows estimates by random-effecs with adjusted country size as the scale variable. All variables are in logs. We always control for time dummies. Note that the coefficient of the scale variable is always positive and significant at the 1% level. In particular, its size and significance are little affected whether we use labor force or GDP as proxies for economic size, whether we use current or constant openness, whether we use *sec* or *ays* to proxy for education, and whether or not we control for TFP, K/L, per capita GDP and its square, land and continent dummies. It is also interesting that the Table reproduces some patterns typical of the other dataset. In particular, the coefficient of the scale variable, which is around 20%, is the same order of magnitude as before (although smaller); it also tends to increase (although by less) when adding more controls. As for the other variables, unlike the other dataset, the coefficient of skill endowment is now always negative and highly significant[44], whereas the coefficients of most controls are insignificantly different from zero.[45]

Table 5 shows the least squares-dummy variables estimates. It essentially replicates the same specifications in Table 4, the main difference being that land area and continent dummies are no longer usable since they are time-invariant. Note that the size of the coefficient of the scale variable is slightly increased; moreover, not surprisingly, the coefficient is now less precisely estimated, although it is always significant at least at the 10% level. Indeed, it is the

[43] More formally, a Hausman specification test was generally insignificant, suggesting the appropriateness of the random-effects estimator. However, the power of this test is rather low when the temporal dimension of the panel is small (three time periods in our case).

[44] The coefficient of education (and in some specifications also the scale coefficient) is generally less precisely estimated when adding an interaction term between openness and education, whose coefficient is however generally insignificant.

[45] As with the other dataset, we have also controlled for the investment share of GDP, which turns out insignificant and irrelevant for the results.

coefficient of education which suffers most from the loss of degrees of freedom induced by the inclusion of country dummies (in some cases it becomes insignificant). Finally, Figure 8 plots the partial relation between the skill premium and adjusted country size, drawn from eq. (2): the relation does not seem to be driven by outliers; note, however, that many countries on the right of the scatterplot are either very small or very large. To see, more generally, whether the significance of the coefficient of $\overline{L}_{it}^{Adj}$ can be affected by the inclusion of very small or very large countries, we rerun eqs. (2) after dropping the largest and smallest countries in the sample (USA, India, Japan, Fiji, Luxembourg, Malta, Cyprus and Panama). The results are shown in columns (5): surprisingly, despite the further loss of degrees of freedom, the coefficients of the scale variable are still significant (at the 8% and 5% levels, respectively), are larger in magnitude (around 25%) and are almost identical when using labor force or GDP.[46]

The good news for our theory end here. Table 6 reports some disappointing results. When we run ASW-like regressions by random-effects and LSDV, the coefficients of our variables of interest turns out generally insignificant. One reason why in this case, unlike with the other data, our synthetic scale variable is always significant whereas its components are not is that with a smaller sample of countries the payoff from using a more parsimonious specification of the scale effect is probably much higher.[47]

4.2 Evidence from other studies

Other empirical studies lend indirect support to our results. Antweiler and Trefler (2002), using trade data for 71 countries and 5 years, show that a rise in output tends to increase the relative demand for skilled workers. Our theoretical model provides an explanation for their finding. Historical evidence seems consistent with a skill-biased scale effect too: Lindert and Williamson (2001), for example, show that inequality widened during globalization booms and after massive immigration, whereas it decreased in the period 1914-1950 of protectionism and in the presence of massive emigration. Likewise, Goldin and Katz (1999) shows that periods of narrowing of the wage structure in the US during the first half of the Twenitieth

[46] Results do not change when dropping only the largest or smallest countries from the sample.

[47] To have a sense of how plausible this explanation can be, we have rerun, with our sample of 44 countries observed between 1970 and 1990, equations (1) and (4) in Table 4 of ASW (2000), where the growth rate of per capita GDP is regressed on *country size* (GDP or population), *openness* and *openness*country size*. For sake of comparison, we have also regressed the growth rate of per capita income on *adjusted country size*, $\overline{L}_i^{Adj}$, with $\overline{L}_i$ proxied by both GDP and labor force. Interestingly, we found that, while five out of six coefficients are insignificant in the ASW-regressions (one also wrong signed), our synthetic scale variable is in both cases significant beyond the 1% level. This suggests that ASW-like regressions may not yield significant results in small samples even when the underlying correlations are strong in larger samples.

century coincided with major economic disruptions. After the wage compression that followed immediately the Second World War (1939-1949), returns to skill remained fairly stable (or even increasing) in the US and fell again during the turbolent years of the Seventies. Since then, skill premia have been on the upward trend. Note that such a behavior of relative wages would be hard to explain, given the steady increase in the supply of skilled workers throughout the century, unless some other mechanism, like the one we suggest, had continuously raised the demand for skill. Finally, Hine and Wright (1998) report indirect evidence in support of the mechanism illustrated in the paper. With reference to the United Kingdom, they estimate the magnitude of trade-induced productivity effects. Their most interesting result is that trade with other OECD countries has a much stronger effect on productivity than trade with developing countries. This is consistent with our model, *in primis*, because the economic size of the OECD countries (and therefore the trade-generated scale effect) is much larger than that of developing countries; *in secundis*, because the UK trade with advanced countries is mainly intra-industry trade in skill-intensive goods characterized by strong scale economies (thereby the more pronounced productivity gain).

5 Concluding Remarks

The most original result of our analysis is to show that the scale of an economy can be a key determinant of wage inequality. This is a general result which applies to different contexts. In this paper, we have emphasized the role played by a trade-induced scale effect, instead of country-specific scale effects, such as factor accumulation or technical progress. A first reason for this focus is policy relevance. Trade is the only scale variable that can change abruptly as a consequence of policy reform. Second, if globalization goes far enough, factor prices will mainly be determined at the world level and country-specific variables will lose their importance. Third, trade is fundamental in our story because the scale effect operates through the increase in the number of available intermediates made possible by some form of trade. Finally, our framework shows that a "new trade theory" explanation based on intra-industry trade may reconcile the increase in wage inequality with the empirical evidence often used to discredit more traditional trade explanations. We consider this as an important result per se. Our empirical findings lend support to this choice of emphasis, as they suggest that a measure of country size adjusted for the trade regime is a major determinant of wage inequality across countries and over time.

We have derived our results for a specific market structure (monopolistic competition) and specific functional forms on the basis of our reading of the empirical evidence, to have a sense of the quantitative significance of the effect we discuss. Much of the debate on trade and inequality is, in fact, centered on the magnitude of the trade-induced effects. But our model is a specific example of a more general principle, surprisingly neglected in the debate: as long as the activities performed by skilled workers enjoy stronger returns to scale than those performed by the unskilled, and the elasticity of substitution among them is non-unitary, any trade-induced increase in market size is non-neutral to income distribution.

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6 Appendix

6.1 The General Model

We study now the more general case in which each good is a Cobb-Douglas composite of H, L and K. We assume that the total cost function of a single variety produced in sector i is:

$$TC_i = (F_i + c_i y_i) r^{\gamma} (w_h^{\alpha_i} w_l^{1-\alpha_i})^{1-\gamma}, \tag{27}$$

where r is the rental rate, γ is the share of capital in total cost, and α_i $(i = h, l)$ is the wage-bill share of skilled workers in sector i. We assume that $\alpha_h > \alpha_l$, namely that sector h is skill-intensive relative to sector l. The relative price of skill-intensive varieties implied by (27) and profit maximization becomes:[48]

$$\frac{p_h}{p_l} = \frac{r^{\gamma}(w_h^{\alpha_h} w_l^{1-\alpha_h})^{1-\gamma}}{r^{\gamma}(w_h^{\alpha_l} w_l^{1-\alpha_l})^{1-\gamma}} = \omega^{(1-\gamma)(\alpha_h - \alpha_l)}. \tag{28}$$

Free-entry and the simplifying assumption $F_i = 1/\sigma_i$ fix the scale of production of each variety to one: $y_i = 1$. Equations (2), (9) and (10) are unchanged; together with (28) they imply:

$$n_h^{\frac{\sigma_h - \epsilon}{\epsilon(\sigma_h - 1)}} \omega^{(1-\gamma)(\alpha_h - \alpha_l)} = n_l^{\frac{\sigma_l - \epsilon}{\epsilon(\sigma_l - 1)}}. \tag{29}$$

The demand for each factor can be found using Shephard's lemma on the total cost function (27). After setting w_l as the numeraire, the conditions for full employment of capital, skilled and unskilled workers become:

$$\begin{aligned}
K &= \gamma r^{\gamma-1} \omega^{(1-\gamma)\alpha_h} n_h + \gamma r^{\gamma-1} \omega^{(1-\gamma)\alpha_l} n_l \\
H &= (1-\gamma)\alpha_h r^{\gamma} \omega^{(1-\gamma)\alpha_h - 1} n_h + (1-\gamma)\alpha_l r^{\gamma} \omega^{(1-\gamma)\alpha_l - 1} n_l \\
L &= (1-\gamma)(1-\alpha_h) r^{\gamma} \omega^{(1-\gamma)\alpha_h} n_h + (1-\gamma)(1-\alpha_l) r^{\gamma} \omega^{(1-\gamma)\alpha_l} n_l.
\end{aligned}$$

Solving for n_h and n_l gives:

$$\begin{aligned}
n_i &= \frac{(1-\alpha_j) H\omega - \alpha_j L}{(1-\gamma)(\alpha_i - \alpha_j)\omega^{\alpha_i(1-\gamma)}} \left(\frac{\gamma}{1-\gamma} \frac{L + H\omega}{K} \right)^{-\gamma} \\
&= \frac{\overline{L}^{1-\gamma} K^{\gamma} \left[(1-\alpha_j)\theta\omega - \alpha_j(1-\theta) \right] (1-\theta+\theta\omega)^{-\gamma}}{(1-\gamma)^{1-\gamma}\gamma^{\gamma}(\alpha_i - \alpha_j)\omega^{\alpha_i(1-\gamma)}},
\end{aligned}$$

[48] Prices are a markup over marginal cost, and we have again used the normalization $c_i = \left(1 - \frac{1}{\sigma_i}\right)$.

for $i, j = l, h$, $i \neq j$, $\overline{L} = H + L$ and $\theta = H/\overline{L}$. Simple derivation yields:

$$\frac{\partial n_h}{\partial \omega} > 0, \frac{\partial n_l}{\partial \omega} < 0, \frac{\partial n_h}{\partial \theta} > 0, \frac{\partial n_l}{\partial \theta} < 0. \tag{30}$$

These partial derivatives come from the production side of the economy. They imply that the higher the supply of one factor, the larger the size of the sector which uses that factor intensively, and that the larger the size of one sector, the higher the relative reward for the factor which is used intensively in that sector. Using the expressions for n_h and n_l in (29) and differentiating it with respect to θ, K and $\overline{L}$, we find the elasticity of the skill premium:

$$\frac{d\omega}{\omega} = \frac{\frac{(\epsilon-1)(\sigma_l-\sigma_h)}{(\sigma_h-1)(\sigma_l-1)}\left[\gamma\frac{dK}{K} + (1-\gamma)\frac{d\overline{L}}{\overline{L}}\right] - \left(\frac{\sigma_h-\epsilon}{\sigma_h-1}\frac{\partial n_h}{\partial \theta}\frac{\theta}{n_h} - \frac{\sigma_l-\epsilon}{\sigma_l-1}\frac{\partial n_l}{\partial \theta}\frac{\theta}{n_l}\right)\frac{d\theta}{\theta}}{(1-\gamma)(\alpha_h-\alpha_l)\epsilon + \frac{\sigma_h-\epsilon}{\sigma_h-1}\frac{\partial n_h}{\partial \omega}\frac{\omega}{n_h} - \frac{\sigma_l-\epsilon}{\sigma_l-1}\frac{\partial n_l}{\partial \omega}\frac{\omega}{n_l}}.$$

Given the inequalities in (30) and our assumption $1 < \epsilon < \sigma_h < \sigma_l$, it can be seen that the skill premium is increasing in the scale and decreasing in the share of skilled workers. Equations (14) and (20) are all special cases of this formula.

6.2 Elasticity of Substitution

Finally, it is possible to show that the aggregate elasticity of substitution between skilled and unskilled workers (holding the other variables constant) is given by:

$$\varepsilon_w = -\frac{d(H/L)}{d\omega}\frac{\omega}{H/L}\bigg|_{n_h,n_l,K_h,K_l} = \frac{(\alpha_h-\alpha_l)(\epsilon-1)}{\left(\frac{\alpha_h}{1-\alpha_h}\frac{L}{H\omega}-1\right)^{-1} + \left(1-\frac{\alpha_l}{1-\alpha_l}\frac{L}{H\omega}\right)^{-1}} + 1.$$

Rearranging, we can write the elasticity of substitution in consumption (ϵ) as a function of the elasticity of substitution in production (ε_w):

$$\epsilon = 1 + \frac{(\varepsilon_w - 1)}{\alpha_h - \alpha_l}\left[\left(\frac{\alpha_h}{1-\alpha_h}\frac{L}{H\omega} - 1\right)^{-1} + \left(1 - \frac{\alpha_l}{1-\alpha_l}\frac{L}{H\omega}\right)^{-1}\right].$$

Note that $\varepsilon_w > 1$ implies $\epsilon > 1$ and that $\varepsilon_w = \epsilon$ if $\alpha_h = 1$ and $\alpha_l = 0$, as in the model with extreme factor intensities in the main text.

6.3 The Data

Data on Mincerian returns to education come from Banerjee and Duflo (2004), who provide data for 77 countries. For six of these countries we do not have data on our key independent variables. We are left with 71 observations. For eight of them the Barro-Lee dataset does not provide data on average years of schooling and we therefore use data on average years of schooling coming from the World Bank, as reported in Banerjee and Duflo. The list of countries is the following (in parenthesis we specify the year for which the data are collected; an asterisk denotes the countries for which we use data on education from the World Bank): Argentina (1989), Australia (1989), Austria (1993), Bolivia (1993), Botswana (1979), Brazil (1998), Cameroon (1995), Canada (1989), Chile (1989), *China (1993), Colombia (1989), Costa Rica (1992), *Cote d'Ivoire (1987), Cyprus (1994), Denmark (1990), Dominican Republic (1989), Ecuador (1987), Egypt (1997), El Salvador (1992), *Estonia (1994), Ethiopia (1997), Finland (1993), France (1977), Germany (1988), Ghana (1999), Greece (1993), Guatemala (1989), Honduras (1991), Hong Kong (1981), *Hungary (1987), India (1995), Indonesia (1995), Iran (1975), Israel (1979), Italy (1987), Jamaica (1989), Japan (1988), Kenya (1995), Korea, Republic of (1986), Malaysia (1979), Mexico (1997), *Morocco (1970), Nepal (1999), Netherlands (1994), Nicaragua (1996), Norway (1995), Pakistan (1991), Panama (1990), Paraguay (1990), Peru (1990), Philippines (1998), *Poland (1996), Portugal (1991), Singapore (1998), South Africa (1993), Spain (1991), Sri Lanka (1981), Sweden (1991), Switzerland (1991), *Taiwan (1998), *Tanzania (1991), Thailand (1989), Tunisia (1980), USA (1995), Uganda (1992), United Kingdom (1987), Uruguay (1989), Venezuela (1992), *Vietnam (1992), Zambia (1995), Zimbabwe (1994).

Data on manufacturing skill premia come from the UN - General Industrial Statistics database. Our sample comprises the following 44 countries (in parenthesis, we specify the years for which data are collected): Australia (1970, 1980, 1987), Austria (1970, 1980, 1990), Bangladesh (1970, 1979, 1989), Canada (1970, 1980, 1990), Chile (1970, 1979, 1990), Colombia (1970, 1980, 1990), Cyprus (1980, 1990), Czechoslovakia (1970, 1980, 1990), Denmark (1970, 1980, 1990), Ecuador (1970, 1979), Egypt (1980, 1988), El Salvador (1971, 1978), Ethiopia[49] (1980, 1988), Fiji (1979, 1990), Finland (1970, 1980, 1990), Greece (1970, 1977, 1990), Guatemala (1973, 1978, 1988), Hungary (1970, 1980, 1990), India (1969, 1978, 1988), Iran (1969, 1980), Ireland (1970, 1978, 1989), Italy (1970, 1980, 1989), Japan (1970, 1981, 1990), Korea, Republic of (1970, 1979, 1990), Luxembourg (1970, 1980, 1990), Malaysia (1983, 1990), Malta (1970, 1980, 1988), Mexico (1986, 1990), New Zealand (1970, 1978), Norway (1970, 1980), Pakistan (1981, 1988), Panama (1970, 1979, 1989), Peru (1972, 1980, 1988), Philippines (1970, 1977, 1987), Portugal (1971, 1980), Spain (1980, 1990), Sweden (1970, 1980, 1990), Tanzania[50] (1970, 1981, 1985), Turkey (1969, 1980, 1990), USA (1970, 1980, 1990), United Kingdom (1970, 1980, 1990), Uruguay (1980, 1988), Venezuela (1970,

[49] School attainment is available for 1995 only

[50] School attainment is proxied by the average for sub-Saharan countries.

1979, 1990),West Germany (1970, 1980, 1990).

Finally, to compute the total factor productiviy (TFP), we follow Hall and Jones (1999). First, we estimate the capital stock using the permanent inventory method (we assume a depreciation rate of 6 percent), and then compute, for each country i and year t, the log of TFP as: $\ln TFP_{it} = \ln(y_{it}) - \frac{\alpha}{1-\alpha}\ln(\frac{K_{it}}{L_{it}}) - \ln(h_{it})$, where y is GDP per worker, K/Y is the capital/output ratio, $\alpha = 1/3$, and h is human capital per worker ($h_{it} = e^{\phi(E_{it})}$, where E stands for years of education and ϕ is a piecewise linear function specified as in Hall and Jones).

Table 1. Scale and wage inequality across countries (Scale = $\overline{L}_i^{Adj} = \overline{L}_i + Op_i \sum_{j \neq i}^{N} Op_j \overline{L}_j$)

Dependent variable: Mincerian returns to education (ω_i)

Indep. Variables	(1)	(1')	(2)	(2')	(3)	(3')	(4)	(4')
	labor force	GDP	labor force	GDP	labor force	GDP	labor force	GDP
Scale ($\overline{L}_i^{Adj}$)	.224**	.259*	.345**	.456***	.353**	.470***	.278**	.497***
	(.101)	(.143)	(.138)	(.162)	(.146)	(.174)	(.130)	(.138)
Skill endowment (θ_i)	-.129	-.215	-.119	-.144	-.081	-.145	.020	-.011
	(.130)	(.134)	(.166)	(.170)	(.139)	(.140)	(.231)	(.211)
Controls:								
TFP			-.073	-.112	-.052	-.119	-.040	-.061
			(.075)	(.073)	(.074)	(.070)	(.306)	(.279)
K/L			.016	-.012			.140	.129
			(.062)	(.062)			(.152)	(.142)
T/L			.077**	.077**	.077**	.076**	.041	.051
			(.036)	(.033)	(.037)	(.034)	(.043)	(.039)
Inv. Share of GDP					-.027	-.040		
					(.088)	(.089)		
GDP p.c.							1.916	2.149
							(1.510)	(1.344)
GDP p.c. squared							-.128	-.144**
							(.072)	(.063)
# observations	69	71	66	66	66	66	66	66
R-squared	.09	.09	.16	.18	.16	.18	.31	.37

Notes: all variables in logs. OLS estimation with White-robust standard errors in parentheses. ***,**,* = significant at the 1, 5 and 10-percent levels, respectively. All equations include five-years time dummies (observations span from the 70s to the 90s). labor force (GDP) = economic size proxied by labor force (GDP) in computing adjusted country size. *Op* = *openc*/2 in computing adjusted country size. θ_i = *ays*. Data sources: Banerjee and Duflo (2004), PWT (5.6 and 6.1), Barro-Lee and WDI.

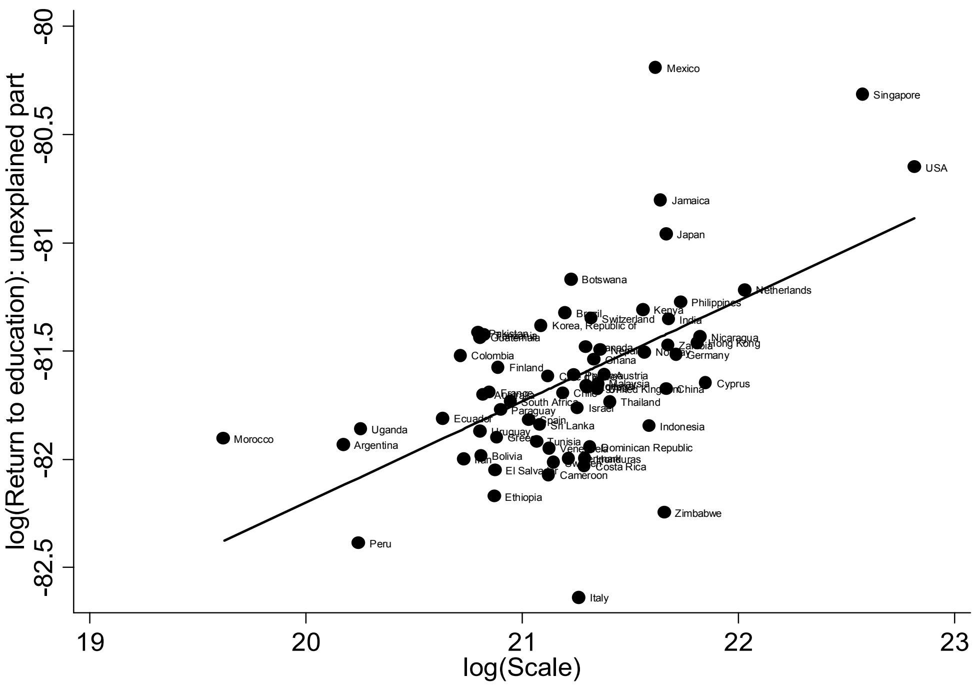

Figure 4 – Scale ($\overline{L}_i^{Adj}$) and Mincerian returns to education

Table 2. Scale and wage inequality across countries (Scale = $\overline{L}_i^{Adj}$; robustness checks)

Dependent variable: Mincerian returns to education (ω_i)

Indep. Variables	(1)	(1')	(2)	(2')	(3)	(3')	(4)	(4')
	lab. force, infl. obs	*GDP, infl. obs*	*lab. force, sec*	*GDP, sec*	*lab. force, openk*	*GDP, openk*	*lab. force, continent dummies*	*GDP, continent dummies*
Scale ($\overline{L}_i^{Adj}$)	.211*	403***	.408***	.514***	.222**	.357***	.296**	.453***
	(.125)	(.156)	(.154)	(.145)	(.103)	(.124)	(.135)	(.159)
Skill endowment (θ_i)	-.025	-.019	-.031	-.038	.039	.034	-.041	-.033
	(.230)	(.214)	(.137)	(.132)	(.230)	(.212)	(.254)	(.230)
Controls:								
TFP	-.142	-.126	-.129	-.118	-.049	-.057	-.057	-.067
	(.312)	(.288)	(.253)	(.251)	(.301)	(.282)	(.292)	(.275)
K/L	.111	097	.106	.113	.143	.139	.135	.104
	(.149)	(.141)	(.143)	(.142)	(.151)	(.144)	(.147)	(.139)
T/L	.055	.067*	.054	.049	.026	.027	.032	.057
	(.038)	(.035)	(.039)	(.036)	(.041)	(.039)	(.054)	(.052)
GDP p.c.	2.61*	2.560*	2.180*	2.336*	2.041	2.261*	.523	.672
	(1.487)	(1.358)	(1.308)	(1.260)	(1.478)	(1.365)	(1.559)	(1.457)
GDP p.c. squared	-.164**	-.164***	-.137**	-.151**	-.135*	-.151**	-.034	-.044
	(.070)	(.064)	(.0645)	(.061)	(.070)	(.065)	(.081)	(.075)
# observations	64	64	63	63	66	66	66	66
R-squared	.38	.41	.31	.35	.31	.35	.45	.48

Notes: all variables in logs. OLS estimation with White-robust standard errors in parentheses. ***,**,* = significant at the 1, 5 and 10-percent levels, respectively. All equations include five-years time dummies (observations span from the 70s to the 90s). Eqs. (4) also include continent dummies. labor force (GDP) = economic size proxied by labor force (GDP) in computing adjusted country size. *Op* = *openc*/2 in computing adjusted country size, except in Eqs. (3), where Op = *openk*/2. θ_i = *ays*, except in Eqs. (2), where θ_i = *sec*. Eqs. (1) exclude observations on USA and Singapore. Data sources: Banerjee and Duflo (2004), PWT (5.6 and 6.1), Barro-Lee and WDI.

Table 3. Scale and wage inequality across countries (Scale = Country size + Openness)

Dependent variable: Mincerian returns to education (ω_i)

Indep. Variables	(1)	(1’)	(1’’)	(1’’’)	(2)	(2’)	(3)	(3’)	(4)	(4’)
	labor force	*GDP*	*GDP, sec*	*GDP, sec, infl obs*	*labor force*	*GDP*	*labor force, sec*	*GDP, sec*	*labor force, openk*	*GDP, openk*
Country size	.091*	.138*	.224***	.244***	.180***	.252***	.239***	.294***	.178***	.218***
	(.051)	(.079)	(.065)	(.072)	(.061)	(.066)	(.072)	(.070)	(.057)	(.061)
Openness	1.100	3.671	7.041***	7.304***	1.937**	5.880**	2.554**	6.601***	2.095**	5.277**
	(1.078)	(2.886)	(2.517)	(2.501)	(.953)	(2.514)	(1.117)	(2.539)	(.916)	(2.299)
Openness Country size*	-.113	-.193	-.374***	-.377***	-.184	-.295**	-.259*	-.333 **	-.214*	-.268**
	(.137)	(.156)	(.136)	(.130)	(.122)	(.138)	(.141)	(.139)	(.115)	(.126)
Skill endowment θ_i	-.118	-.213	-.165*	-.184**	.087	.064	.039	.029	.102	.089
	(.139)	(.144)	(.092)	(.084)	(.233)	(.199)	(.124)	(.105)	(.232)	(.204)
Controls:										
TFP					-.049	-.032	-.183	-.141	-.066	-.051
					(.322)	(.268)	(.255)	(.220)	(.316)	(.274)
K/L					.109	.083	.059	.031	.118	.095
					(.159)	(.146)	(.150)	(.140)	(.160)	(.148)
T/L					.079**	.068**	.083**	.072**	.053 *	.040
					(.036)	(.034)	(.035)	(.033)	(.032)	(.031)
GDP p.c.					2.255	1.778	2.86**	2.189*	2.296	1.896
					(1.504)	(1.323)	(1.321)	(1.200)	(1.460)	(1.337)
GDP p.c. squared					-.148**	-.123*	-.176***	-.142**	-.151**	-.130 **
					(.071)	(.063)	(.066)	(.061)	(.067)	(.064)
# observations	69	71	63	61	66	66	63	63	66	66
R-squared	.09	.11	.19	.19	.40	.44	.39	.43	.40	.42

Notes: as in ASW, all variables except openness in logs. OLS estimation with White-robust standard errors in parentheses. ***,**,* = significant at the 1, 5 and 10-percent levels, respectively. All equations include five-years time dummies (observations span from the 70s to the 90s). labor force (GDP) = country size proxied by labor force (GDP). Openness = *openc*, except in Eqs. (4), where Openness = *openk*. θ_i = *ays*, except in Eqs. (1’’)-(1’’’) and (3)-(3’), where θ_i = *sec*. Eq. (1’’’) excludes observations on Hong Kong and Singapore. Data sources: Banerjee and Duflo (2004), PWT (5.6 and 6.1), Barro-Lee and WDI.

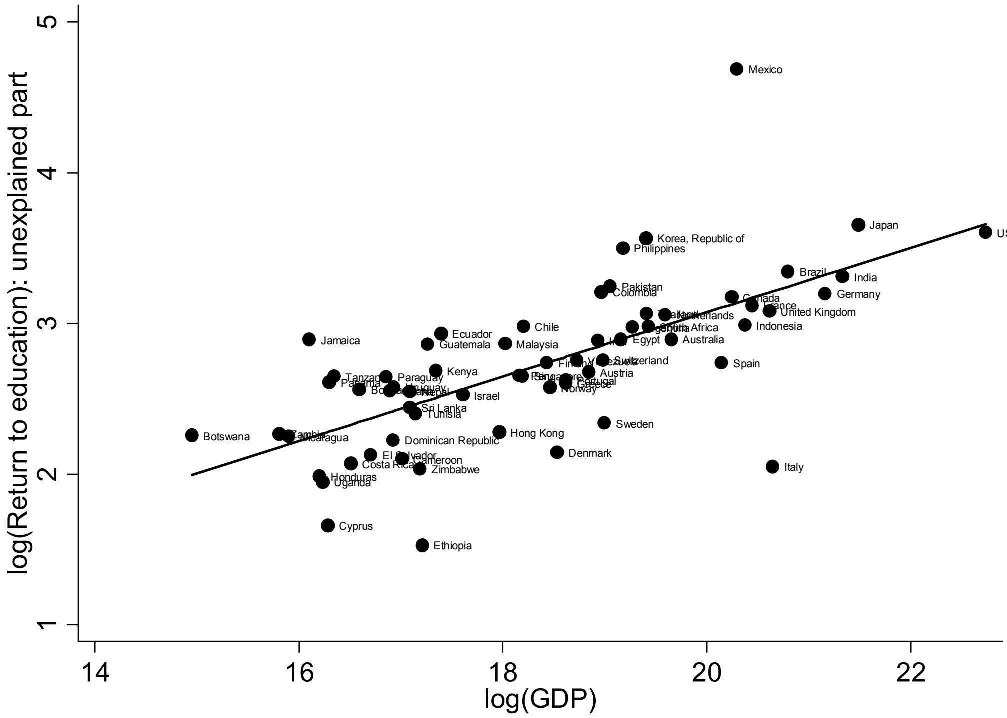

Figure 5 – Scale (GDP) and Mincerian returns to education

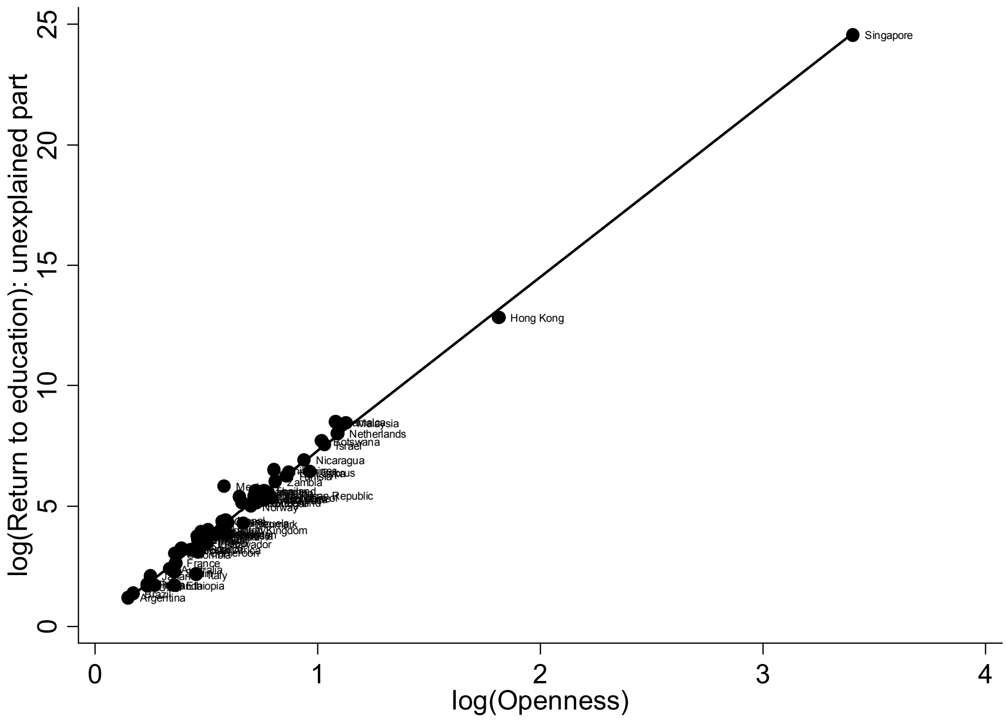

Figure 6 – Openness and Mincerian returns to education

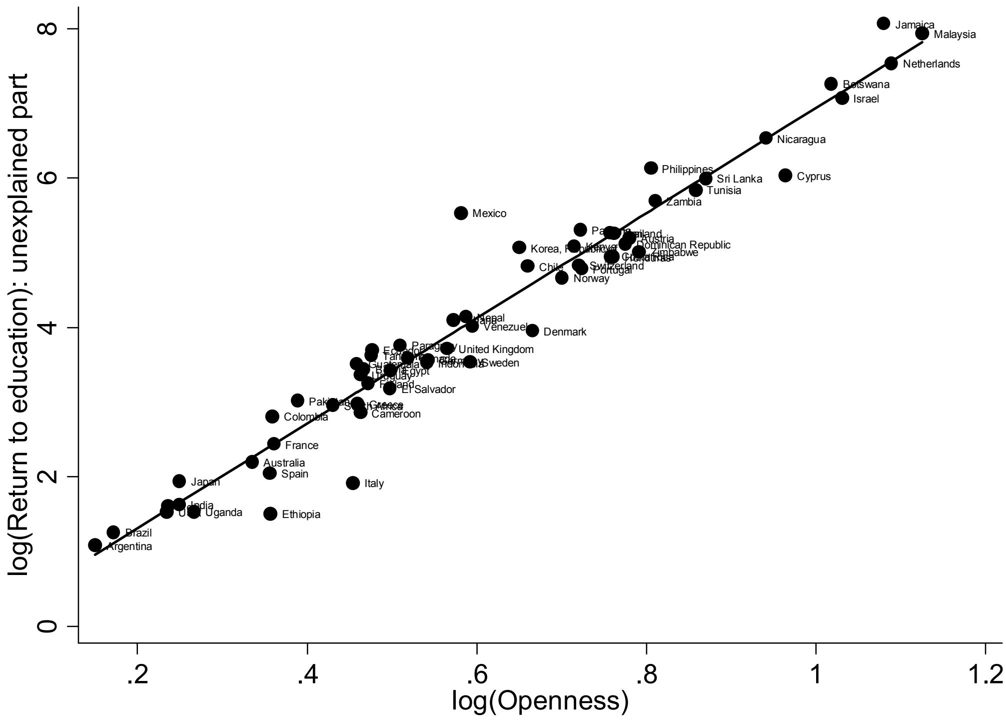

Figure 7 – Openness and Mincerian returns to education (no outliers)

Table 4. Scale and wage inequality across countries (Scale = $\overline{L}_{it}^{Adj}$; Random-Effects)

Dependent variable: Skill premia (ω_{it})

Indep. Variables	(1)	(1')	(2)	(2')	(3)	(3')	(4)	(4')	(5)	(5')
	lab. for.	*GDP*	*lab. for.*	*GDP*	*lab. for.*	*GDP*	*lab. for., sec*	*GDP, sec*	*lab. for., openk*	*GDP, openk*
Scale ($\overline{L}_{it}^{Adj}$)	.160***	.181***	.192***	.213***	.231***	.245***	.224***	.234***	.206***	.245***
	(.062)	(.062)	(.071)	(.075)	(.071)	(.079)	(.071)	(.079)	(.071)	(.079)
Skill endowment	-.322***	-.373***	-.315**	-.354***	-.354***	-.385***	-.227***	-.241***	-.348***	-.385***
(θ_{it})	(.067)	(.070)	(.136)	(.134)	(.133)	(.133)	(.081)	(.081)	(.138)	(.133)
Controls:										
TFP			.107	.078	-.029	-.060	.065	.046	-.105	-.060
			(.161)	(.158)	(.156)	(.155)	(.131)	(.131)	(.155)	(.155)
K/L			.018	.014	-.028	-.044	-.005	-.019	-.090	-.044
			(.095)	(.093)	(.090)	(.089)	(.087)	(.087)	(.090)	(.089)
GDP p.c.			.593	.547	.825	.605	.402	.147	1.407*	.605
			(.848)	(.847)	(.839)	(.864)	(.724)	(.759)	(.838)	(.864)
GDP p.c. squared			-.039	-.037	-.039	-.028	-.020	-.007	-.067	-.028
			(.041)	(.041)	(.041)	(.042)	(.037)	(.038)	(.042)	(.042)
T					-.021	-.015	-.015	-.009	-.022	-.015
					(.028)	(.030)	(.027)	(.029)	(.029)	(.030)
Continent dummies	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
# observations	117	117	108	108	108	108	108	108	105	108
# groups	44	44	41	41	41	41	41	41	40	41
R-squared	.23	.24	.26	.27	.55	.53	.57	.55	.55	.53

Notes: all variables in logs. Estimation by random-effects (standard errors in parentheses). ***,**,* = significant at the 1, 5 and 10-percent levels, respectively. Time dummies always included. labor force (GDP) = economic size proxied by labor force (GDP) in computing adjusted country size. *Op* = openc/2 in computing adjusted country size, except in Eqs. (5), where Op = *openk/2*. θ_{itt} = *ays*, except in Eqs. (4), where θ_{it} = *sec*. Data sources: UN-GIS, PWT (5.6 and 6.1), Barro-Lee and WDI.

Table 5. Scale and wage inequality across countries (Scale = $\overline{L}_{it}^{Adj}$; LSDV)

Dependent variable: Skill premia (ω_{it})

Indep. Variables	(1)	(1')	(2)	(2')	(3)	(3')	(4)	(4')	(5)	(5')
	labor force	*GDP*	*labor force*	*GDP*	*lab.for., Sec*	*GDP, sec*	*lab.for., openk*	*GDP, openk*	*lab.for., infl obs*	*GDP, infl obs*
Scale ($\overline{L}_{it}^{Adj}$)	.194*	.206**	.215**	.243**	.227**	.248**	.193*	.193*	.260*	257**
	(.101)	(.105)	(.106)	(.113)	(.107)	(.114)	(.106)	(.110)	(.147)	(.128)
Skill endowment	-.337***	-.377***	-.254	-.295*	-.119	-.132	-.267	-.309*	-.114	-.174
(θ_t)	(.116)	(.114)	(.186)	(.174)	(.103)	(.100)	(.176)	(.164)	(.213)	(.189)
Controls:										
TFP			-.140	-.176	-.074	-.107	-.259	-.285	-.119	-.167
			(.222)	(.199)	(.218)	(.197)	(.229)	(.222)	(.219)	(.198)
K/L			-.130	-.145	-.118	-.138	-.208	-.226	-.164	-.180
			(.152)	(.139)	(.152)	(.138)	(.161)	(.156)	(.150)	(.142)
GDP p.c.			.028	-.169	-.434	-.716	.670	.584	-.336	-.436
			(1.05)	(1.14)	(.958)	(1.08)	(.953)	(.991)	(1.58)	(1.53)
GDP p.c. squared			.018	.029	.041	.057	-.010	-.004	.039	.046
			(.060)	(.063)	(.053)	(.059)	(.057)	(.058)	(.087)	(.085)
# observations	117	117	108	108	108	108	105	105	89	89
# groups	44	44	41	41	41	41	40	40	34	34
R-squared	.92	.93	.93	.93	.93	.93	.93	.93	.94	.94

Notes: all variables in logs. Estimation by least squares-dummy variables with White-robust standard errors in parentheses. ***,**,* = significant at the 1, 5 and 10-percent levels, respectively. Time dummies always included. labor force (GDP) = economic size proxied by labor force (GDP) in computing adjusted country size. *Op* = openc/2 in computing adjusted country size, except in Eqs. (4), where Op = *openk/2*. θ_t = *ays*, except in Eqs. (3), where θ_t = *sec*. Eqs. (5) exclude observations on the smallest and largest countries in the sample. Data sources: UN-GIS, PWT (5.6 and 6.1), Barro-Lee and WDI.

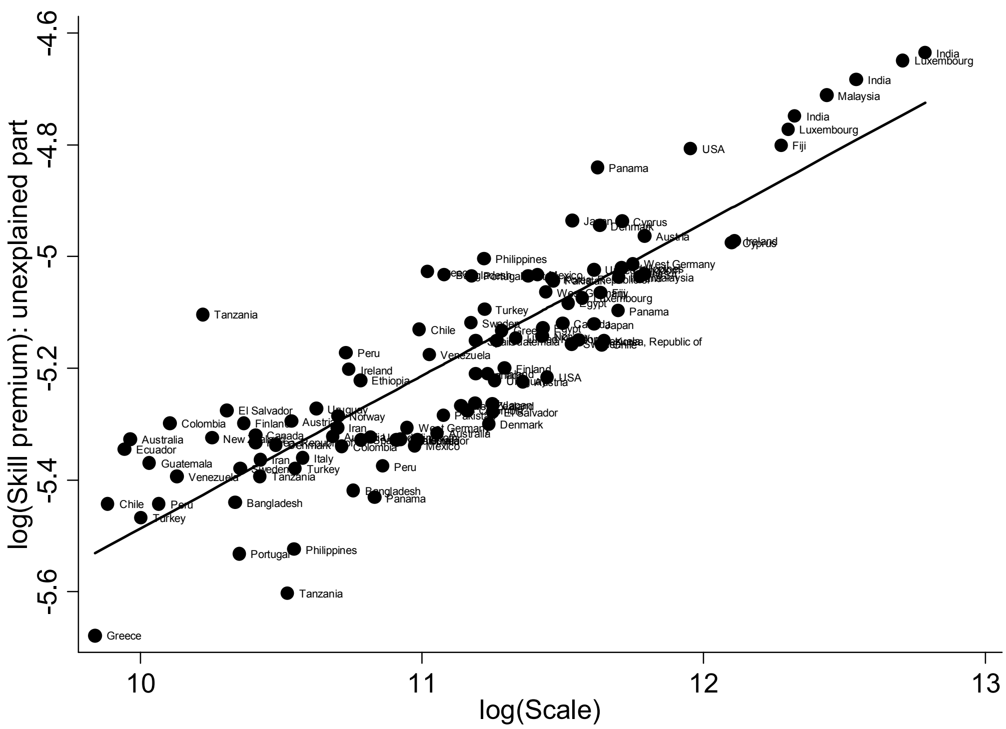

Figure 8 – Scale ($\overline{L}_{it}^{Adj}$) and skill premia

Table 6. Scale and wage inequality across countries (Scale = Country size + Openness). Dependent variable: Skill premia (ω_{it})

Indep. Variables	(1)	(1')	(1'')	(1''')	(2)	(2')	(2'')	(2''')
	lab. for., RE	*GDP,* RE	*lab. for.,* LSDV	*GDP,* LSDV	*lab. for.,* RE	*GDP,* RE	*lab. for.,* LSDV	*GDP,* LSDV
Country size	.003	.011	.120	.126	.019	.014	-.204	-.259
	(.033)	(.032)	(.173)	(.086)	(.049)	(.053)	(.247)	(.273)
Openness	.099	.107	.141	.051	.545*	.668	.551	.372
	(.254)	(.535)	(.455)	(1.05)	(.288)	(.609)	(.476)	(.922)
Openness Country size*	.009	.004	.002	.004	-.029	-.022	-.033	-.007
	(.027)	(.029)	(.049)	(.054)	(.030)	(.033)	(.048)	(.049)
Skill endowment (θ_{it})	-.285***	-.294***	-.304**	-.366***	-.367***	-.374***	-.248	-.202
	(.061)	(.069)	(.143)	(.125)	(.130)	(.132)	(.181)	(.208)
Controls:								
TFP					-.090	-.113	-.283	-.199
					(.149)	(.149)	(.212)	(.188)
K/L					-.072	-.086	-.206	-.167
					(.087)	(.085)	(.147)	(.125)
GDP p.c.					.620	.527	.412	.638
					(.841)	(.840)	(1.15)	(1.20)
GDP p.c. squared					-.024	-.019	.004	-.002
					(.042)	(.042)	(.063)	(.065)
T					-.004	-.006		
					(.036)	(.036)		
Time dummies	No	No	No	No	Yes	Yes	Yes	Yes
# observations	117	117	117	117	108	108	108	108
# groups	44	44	44	44	41	41	41	41
R-squared	.29	.28	.91	.91	.57	.57	.94	.94

Notes: all variables in logs. RE = estimation by random-effects; LSDV = estimation by least squares-dummy variables. Standard errors in parentheses (White-robust in LSDV). ***,**,* = significant at the 1, 5 and 10-percent levels, respectively. Eqs. (2) also control for continent dummies. labor force (GDP) = country size proxied by labor force (GDP). Openness = *openc*. θ_{it} = *ays*. Data sources: UN-GIS, PWT (5.6 and 6.1), Barro-Lee and WDI.