International Trade, Technology, and the Skill Premium*

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Abstract

What are the consequences of international trade on the *skill premium*? We build a multi-country model of international trade that introduces skill intensity differences across firms and sectors and factor endowment differences across countries into an otherwise standard Ricardian model of international trade. In our model, reductions in trade costs affect the relative demand for skill by reallocating factors towards a country's comparative advantage sectors—increasing the skill premium in skill-abundant and decreasing it in skill-scarce countries—and towards more productive and skill-intensive firms within sectors—increasing the skill premium in all countries. Parameterized for 65 countries using firm-, sector-, and aggregate-level data, our model accounts for a number of features of the data including the positive relationship between firm size, export status, and skill intensity. While trade cost reductions raise the real wage for both skilled and unskilled workers in most countries in our model, the percentage point rise in the real wage is two to three times greater for skilled workers than for unskilled workers in the median country. The skill premium rises in almost all countries, even in those that are skill-scarce. Through the lens of our model, three standard alternative approaches in the literature underestimate the rise in the skill premium generated by trade cost reductions in almost all countries, but especially in skill-scarce countries.

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1 Introduction

What are the consequences of international trade on the relative wage of skilled to unskilled workers, i.e. the *skill premium*? Most previous empirical and quantitative studies of the impact of international trade on the skill premium are based on the predictions of the Heckscher-Ohlin model (henceforth H-O). In that model, the ratio of skilled workers, h, to unskilled workers, l, of a sector j producer may be expressed as

$$\frac{h}{l} = \frac{\alpha_j}{1-\alpha_j}\left(\frac{s}{w}\right)^{-\rho},$$

where $\alpha_j \in (0,1)$ is a sector characteristic; s and w are skilled and unskilled wages, respectively; and ρ is the elasticity of substitution between skilled and unskilled workers. According to this theory, reductions in trade costs shift factors of production towards a country's comparative advantage sectors and raise the relative return to the factor that is used intensively in these sectors, a force which we refer to as the *H-O mechanism*. Specifically, international trade increases the skill premium in countries that have a comparative advantage in skill-intensive sectors (high α_j sectors) and decreases it elsewhere. Previous work based on this mechanism has cast doubt on the importance of international trade in affecting the skill premium because the H-O model is qualitatively inconsistent with a range of outcomes both in developed and developing countries: e.g. (i) most factor reallocation occurs within rather than across sectors, as shown in e.g. Berman et. al. (1994); and (ii) inequality has increased in many countries abundant in unskilled labor, as discussed in Goldberg and Pavcnik's (2007) survey of empirical work in developing countries. An alternative interpretation, however, is that the standard H-O model abstracts from other potentially important channels through which trade affects the skill premium; see e.g. Acemoglu (2003).

To allow for such channels, we build a multi-country quantitative trade model that extends the H-O model in two dimensions. First, as in much of the recent trade literature we introduce heterogeneity in productivity z across producers within sectors. Trade liberalization leads to less between-sector factor reallocation towards comparative advantage sectors and more within-sector factor reallocation towards more productive firms the higher is the dispersion of within sector productivity. This first extension helps account for the first qualitative inconsistency of the H-O model.[1] Second, consistent with a body of empirical evidence documenting the fact that within sectors larger and exporting firms tend to be more skill intensive than their smaller and domestic competitors, we allow for skill-biased technology

[1] Bernard et. al. (2007a) introduce firm heterogeneity into the H-O model and show that trade induces factor reallocation within and across sectors. However, as in the standard H-O model, all producers within a sector have the same skill intensity in Bernard et. al. (2007a). Hence, their model does not account for the second inconsistency of the H-O model.

at the producer level.[2] To do so, we introduce a production function such that the equilibrium ratio of skilled workers to unskilled workers of a sector j producer from country i with productivity z is given by

$$\frac{h}{l} = \frac{\alpha_j}{1-\alpha_j}\left(\frac{s_i}{w_i}\right)^{-\rho} z^{\varphi},$$

where φ governs the skill-bias of technology. Factor reallocation towards higher productivity firms raises the relative demand for skill within sectors and the skill premium if $\varphi > 0$, a force which we refer to as the *skill-biased technology mechanism.* This tends to raise the skill premium in all countries and helps account for the second qualitative inconsistency of the H-O model.[3] We discipline our choice of φ using data on the elasticity of skill intensity to plant and firm size in Mexico, Brazil, and the US.

The H-O and skill-biased technology mechanisms do not operate in isolation. If technology is skill biased, the same dispersion of productivity z across sectors leads to higher unit cost dispersion across firms in more skill-intensive sectors. Intuitively, if technology is biased towards skilled workers, then productivity differences are magnified in sectors hiring relatively more of them. This has the following implications. First, trade shares are higher in more skill-intensive sectors. We find support for this prediction in US data. Second, more trade in more skill-intensive sectors contributes to reallocating factors towards those sectors, raising the relative demand for skill and the skill premium in all countries in response to a reduction in trade costs. Third, an increase in the skill premium from trade liberalization can be accompanied by a reduction in the relative price of skill-intensive sectors, as found by Lawrence and Slaughter (1993). Finally, in response to reductions in trade costs, the extent of within-sector factor reallocation is greater in more skill-intensive sectors in all countries. Hence, the interaction between observed variation in skill intensities across sectors and across firms within sectors shapes the impact of trade on the skill premium and also helps account for a range of additional facts.

We embed the H-O and skill-biased technology mechanisms into an otherwise standard heterogeneous firm quantitative model of international trade—Bernard et. al. (2002), henceforth BEJK.[4] Because the sign and strength of the impact of these mechanisms on the skill

[2] See e.g. Bernard et. al. (2007b) for evidence for the US, Verhoogen (2008) for Mexico, Alcalá and Hernández (2009) for Spain, Molina and Muendler (2009) for Brazil, and Bustos (20011) for Argentina.

[3] In a simple extension of our model either with multi-product firms or international task trade the skill-biased technology mechanism also operates within the boundary of the firm. Hence, skill intensity rises in trading firms relative to domestic firms, as found empirically for Argentinian firms in Bustos (2011). In our parameterization we match plant- and firm-level cross-sectional data, and therefore abstract from this within firm reallocation.

[4] To link firms in our model to firms in the data, we assume Bertrand competition, which uniquely determines firm size, as in BEJK, rather than perfect competion, as in Eaton and Kortum (2002), henceforth EK. While the economic forces are similar to those in our model, we do not use a model with monopolistic competition with fixed costs as in Melitz (2003) to minimize the number of parameters.

premium depend on bilateral trade volumes with each trade partner, we parametrize a 65-country version of our model to match, among other moments of the data, relative country sizes and bilateral merchandise exports in 2005-2007. Unfortunately, our model with skill-biased technology does not give rise to a closed-form gravity equation at any level of aggregation. Hence, we cannot use the now-standard approach introduced in Dekle et. al. (2007) for computing the general equilibrium effect of changes in trade costs between equilibria without having to solve for trade costs or productivities in the original equilibrium.[5] Instead, we provide a new computational approach that quite accurately matches bilateral exports but does not require an analytic gravity equation at any level of aggregation. This approach, which allows for asymmetric trade costs and trade imbalances, may be used in other applications that do not yield analytic gravity.

We use the parameterized model to conduct a series of counterfactuals, moving countries from autarky to the 2005-2007 baseline parameterization and reducing trade costs ten percent from the baseline. To focus on the direct effect of such changes in trade costs we hold endowments and technologies fixed. Reducing trade costs in our model has the following implications. First, real wages rise for both factors in most countries. Second, however, the percentage point rise in the real wage is two to three times greater for skilled workers than for unskilled workers in the median country. Real wages rise more for skilled workers—i.e. the skill premium rises—in almost all countries. For example, if labor is fully mobile between sectors the maximum, minimum, and mean changes in the skill premium moving each country from autarky to the baseline are about +20%, +2%, and +8%, respectively. The skill premium rises in all countries, even in skill-scarce countries such as China, because the change in relative demand for skill resulting from reallocating factors towards comparative advantage sectors (the H-O mechanism) is smaller than the increase in relative demand for skill resulting from the combination of reallocating factors towards more productive firms within sectors (the skill-biased technology mechanism) and towards more skill-intensive sectors in all countries (the interaction between the two mechanisms). Third, the impact of reductions in trade costs on the rise in the skill premium implied by our model varies systematically with country characteristics. It is greater in smaller countries and in more open countries, but, in contrast to the H-O model, not necessarily in skill-abundant countries like the US. Even in countries in which the change in the skill premium moving from autarky to the baseline is not very large (i.e. 2% in the US), the ratio of the change in the skill

[5] An alternative approach imposes a parametric relationship between bilateral trade costs and bilateral country characteristics; see e.g. EK, Waugh (2010), Ramondo and Rodriguez-Clare (2010), and Fieler (2011). Given that we impose fewer restrictions on trade costs, not surprisingly our approach better matches bilateral exports in the model and the data. Moreover, our algorithm provides an efficient way of iterating over parameter values, which is particularly important given that our model does not yield analytic gravity equations.

premium to the change in the real wage of unskilled workers is quite large (i.e. 1.5 in the US). Fourth, limiting factor mobility between sectors—to capture the short-run effects of trade liberalization in a simple way—magnifies the impact of trade cost reductions on the skill premium.[6] Fifth, there is more within- than between-sector factor reallocation, as found in Haltiwanger et. al. (2004). Sixth, the price of domestically produced skill-intensive goods relative to unskill-intensive goods falls in the US, as found in Lawrence and Slaughter (1993). We also study the implications of growth in China for the skill premium in its trading partners.

Finally, since our model incorporates both the H-O and skill-biased technology mechanisms, we can revisit three alternative approaches that have been used in the literature to study the impact of trade on the skill premium. These alternative approaches, rather than specifying a full GE model, focus on the factor content of trade, as in Katz and Murphy (1992); the extent of between-sector factor reallocation, as in Berman et. al. (1994); and changes in prices, as in Lawrence and Slaughter (1993), Sachs and Shatz (1994), and Feenstra and Hanson (1999). Using data generated by our model, we show that these approaches underestimate by a large margin the rise in the skill premium in skill-abundant countries and predict a counterfactual fall in the skill premium in skill-scarce countries. This is because the first two approaches are designed to capture the H-O mechanism but abstract from the skill-biased technology mechanism, while the third approach assumes—in contrast to our model with variable markups and skill-biased technology—that changes in markups do not vary systematically across sectors.

We are not the first to model the interaction between skill-biased technology, international trade, and inequality; see e.g. Acemoglu (2003) and Yeaple (2005).[7] We build on these approaches by introducing this mechanism into an otherwise standard quantitative trade model in a relatively simple way, with a single new parameter, φ, that we discipline using cross-sectional evidence on the relationship between firm size and skill intensity. We also combine this mechanism with the H-O mechanism, which is important for the reasons discussed above.

Our paper is also related to Burstein, Cravino, and Vogel (2011) and Parro (2011), who build multi-country perfectly competitive models to study the impact of international trade on the skill premium when capital is complementary to skilled labor, a mechanism from which our model abstracts. Different from those papers, our model allows for firm heterogeneity in skill intensity, which allows us to discipline our parameters using cross-sectional firm-level evidence. This firm heterogeneity in skill intensity comes at a cost: our model no longer

[6] See e.g. Kambourov (2009) and Kosar (2011) for micro-founded models of trade liberalizations with limited factor mobility.

[7] See also the work of Epifani and Gancia (2006), Matsuyama (2007), Zeira (2007), Verhoogen (2008), Costinot and Vogel (2009), Harrigan and Reshef (2011), and Vannoorenberghe (2011).

generates analytic gravity equations at any level of aggregation, which forces us to take a different approach to match bilateral trade flows in the model and the data. Finally, relative to Helpman et. al. (2011), we quantify the impact of trade on between-group inequality using a 65-country model, whereas they build and structurally estimate a model (based on Helpman et. al. (2010)) to account for the link between trade and within-group inequality in Brazil. While our objective is to study the impact of trade on between-group inequality, if we allowed for unobservable differences in individuals' effective units of skill, our model would give rise to changes in measured within-group inequality.[8]

2 The Environment

In this section we describe our model, derive its equilibrium conditions, and investigate the two mechanisms linking international trade and the skill premium.

2.1 Model

Our model economy features N countries, indexed by n, and two factors of production, skilled and unskilled labor. Aggregate quantities of inelastically supplied skilled and unskilled labor in country n are L_n and H_n, respectively.[9] We denote their wages by w_n and s_n, respectively. There are J sectors indexed by j. Sectors are divided into merchandise (tradeable) sectors, $j = 1, ..., J_M$, and service (non-tradeable) sectors, $j = J_M + 1, ..., J$.

Preferences: All workers share identical preferences. Utility, denoted by Q_n, aggregates consumption of J_M merchandise sectors and $J - J_M$ service sectors,

$$Q_n = \left(\sum_{j=1}^{J_M} Q_n\left(j\right)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\gamma_n \sigma}{\sigma-1}} \left(\sum_{j=J_M+1}^{J} Q_n\left(j\right)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{(1-\gamma_n)\sigma}{\sigma-1}}.$$

so that a share γ_n of income is spent on merchandise in country n and $\sigma > 0$ is the elasticity of substitution between sectors within merchandise and within services. Sector j consumption

[8] Other models that combine elements of H-O and either Ricardian or Krugman-style models include Trefler (1995), Davis (1995), Davis and Weinstein (2001), Romalis (2004), Chor (2010), and Morrow (2010). Unlike each of these papers, our focus is on the impact of globalization on the skill premium. To the best of our knowledge, we are also the first to embed either the H-O (or skill-biased technology) mechanism into the new multi-country quantitative trade models.

[9] In our counterfactuals we isolate the direct effect of trade on the skill premium and real wages at fixed factor supplies, a reasonable assumption in the short- to medium-run. Allowing for elastic factor supplies would require taking a stand on the technology through which human capital can be accumulated over time in each country.

is a CES aggregate of a continuum of varieties,

$$Q_n(j) = \left(\int_0^1 q_n(\omega, j)^{\frac{\eta-1}{\eta}} \, d\omega \right)^{\frac{\eta}{\eta-1}}$$

where $q_n(\omega, j)$ is the consumption of variety (ω, j) and $\eta > 0$ is the elasticity of substitution between varieties within each sector. Facing prices P_n, $P_n(j)$ and $p_n(\omega, j)$ for the final good, the aggregate sector j good, and variety (ω, j), respectively, utility maximization gives rise to the following demands

$$Q_n(j) = \left(\frac{P_n(j)}{P_n} \right)^{-\sigma} Q_n \tag{1}$$

and

$$q_n(\omega, j) = \left(\frac{p_n(\omega, j)}{P_n(j)} \right)^{-\eta} Q_n(j) \,. \tag{2}$$

Goods within each (ω, j) are perfect substitutes and potentially produced in every country. Consumers purchase each variety from the lowest-cost source in the world.

Production and international trade: In each country there are two potential producers per variety (ω, j). A country n firm in variety (ω, j) that employs h and l units of skilled and unskilled labor, respectively, produces output y according to the constant-returns to scale production function

$$y = A_n(j) \left[\alpha_j^{\frac{1}{\rho}} \left(z^{2\phi} h \right)^{\frac{\rho-1}{\rho}} + (1-\alpha_j)^{\frac{1}{\rho}} \left(z^{2(1-\phi)} l \right)^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}} \tag{3}$$

where $\rho > 0$ is the elasticity of substitution between skilled and unskilled workers at the level of an individual producer, z is the firm-specific productivity, and $A_n(j)$ is the country-sector total factor productivity (TFP). Both $0 \leq \alpha_j \leq 1$ and $0 \leq \phi \leq 1$ shape the skill-intensity of production, as we describe below in section 2.2.[10]

We introduce trade barriers using iceberg transportation costs. We assume that there is no international trade in service sectors. Delivering one unit of a merchandise variety from country i to country n requires producing $\tau_{in} \geq 1$ units in i, where $\tau_{nn} = 1$ for all n. To avoid introducing extra notation, we simply assume $\tau_{in} = \infty$ if $i \neq n$ in any service sector. We abstract from entrepôt trade by assuming that countries cannot re-export imported goods.[11] Let $c_{ink}(\omega, j)$ denote $\tau_{in} \times$ the unit cost of production of the k'th, $k = 1, 2$, most productive

[10] According to this production function the marginal product of skilled relative to unskilled workers varies with firm productivity if $\phi \neq 0.5$ and $\rho \neq 1$, as we discuss in detail below. We follow a large matching literature in which assumptions on production technologies give rise to assortative matching; see e.g. Sattinger (1993).

[11] Therefore, we do not need to impose the triangle inequality $\tau_{in} \leq \tau_{ik}\tau_{kn}$ in our quantitative analysis.

(ω, j) firm in country i,

$$c_{ink}(\omega, j) = \frac{\tau_{in}}{A_i(j)} \left[\alpha_j z^{2\phi(\rho-1)} s_i^{1-\rho} + (1-\alpha_j) z^{2(1-\phi)(\rho-1)} w_i^{1-\rho}\right]^{\frac{1}{1-\rho}}, \tag{4}$$

where z is the productivity of this producer. With $0 \leq \phi \leq 1$, marginal costs are decreasing in z. Each firm draws its firm-specific productivity $z > 0$ from a distribution, which we model as in EK, BEJK, and Alvarez and Lucas (2007). In particular, all firms in all countries draw their productivities from the distribution $u^{-\theta}$, where u is an *i.i.d.* random variable that is exponentially distributed with mean and variance 1 in all countries. A higher value of $\theta > 0$ increases the dispersion of productivity across firms.[12]

Competition and prices: Firms engage in Bertrand competition within each variety. With undifferentiated goods within each (ω, j), each market n is supplied only by the lowest-cost supplier in the world, and this supplier is constrained not to charge a price above the cost of the second-lowest cost supplier. With CES preferences across varieties within a sector, the unconstrained markup of the lowest-cost supplier is $\eta/(\eta-1)$. Denote the first- and second-lowest costs of supplying variety (ω, j) to country n by

$$C_{1n}(\omega, j) = \min_i \{c_{in1}(\omega, j)\}$$

and

$$C_{2n}(\omega, j) = \min\left\{c_{i^*n2}, \min_{i \neq i^*}\{c_{in1}(\omega, j)\}\right\},$$

respectively, where i^* is the country from which the lowest-cost supplier of (ω, j) originates: $C_{1n}(\omega, j) = c_{i^*n1}(\omega, j)$. Hence, the price of variety (ω, j) in country n is the minimum of the constrained and unconstrained prices,

$$p_n(\omega, j) = \min\left\{C_{2n}(\omega, j), \frac{\eta}{\eta-1} C_{1n}(\omega, j)\right\}. \tag{5}$$

Aggregates: Aggregate prices P_n and $P_n(j)$ are

$$P_n = \left(\sum_j P_n(j)^{1-\sigma} d\omega\right)^{1/(1-\sigma)} \tag{6}$$

and

$$P_n(j) = \left(\int_0^1 p_n(\omega, j)^{1-\eta} d\omega\right)^{1/(1-\eta)}. \tag{7}$$

[12] As in EK, we must constrain the values of η and θ to have a well-defined price index when there is a continuum of varieties. In the skill-biased case, however, we cannot derive an analytic expression for this constraint. In all simulations, with a finite number of varieties, the price level is always well defined.

The value of output in country i is defined as

$$Y_i = \sum_j \sum_n \int_0^1 p_n(\omega, j)\, q_n(\omega, j)\, \mathbb{I}_{in}(\omega, j)\, d\omega, \tag{8}$$

where $\mathbb{I}_{in}(\omega, j)$ is an indicator function that equals one if country n imports variety (ω, j) from country i and equals zero otherwise. The values of sales from i to n in sector j and in the aggregate are

$$X_{in}(j) = \int_\omega p_n(\omega, j)\, q_n(\omega, j)\, \mathbb{I}_{in}(\omega, j)\, d\omega \tag{9}$$

and $X_{in} = \sum_j X_{in}(j)$, respectively. Net exports across all sectors in country i, which we allow to be non-zero, are defined as $NX_i = \sum_n (X_{in} - X_{ni})$. Aggregate profits in country i are

$$\Pi_i = \sum_j \sum_n \int_0^1 \left[p_n(\omega, j) - c_{in1}(\omega, j)\right] q_n(\omega, j)\, \mathbb{I}_{in}(\omega, j)\, d\omega. \tag{10}$$

Market clearing: The total quantity produced of each variety (ω, j) in country i must equal its world demand

$$y_i(\omega, j) = \sum_n \tau_{in} q_n(\omega, j)\, \mathbb{I}_{in}(\omega, j). \tag{11}$$

Labor market clearing in each country requires

$$L_i = \sum_j \sum_n \int_0^1 l_{in}(\omega, j)\, d\omega \tag{12}$$

and

$$H_i = \sum_j \sum_n \int_0^1 h_{in}(\omega, j)\, d\omega, \tag{13}$$

where

$$\begin{aligned} l_{in}(\omega, j) &= \left(\tfrac{\tau_{in}}{z^{2(1-\phi)} A_i(j)}\right)^{1-\rho} (1-\alpha_j)\, w_i^{-\rho} c_{in1}(\omega, j)^\rho\, q_n(\omega, j)\, \mathbb{I}_{in}(\omega, j) \\ h_{in}(\omega, j) &= \left(\tfrac{\tau_{in}}{z^{2\phi} A_i(j)}\right)^{1-\rho} \alpha_j s_i^{-\rho} c_{in1}(\omega, j)^\rho\, q_n(\omega, j)\, \mathbb{I}_{in}(\omega, j) \end{aligned} \tag{14}$$

are the amounts of unskilled and skilled labor, respectively, used by the low-cost country i firm in selling variety (ω, j) in country n.

The budget constraint in each country n satisfies

$$P_i Q_i = (s_i H_i + w_i L_i + \Pi_i)(1 - nx_i), \tag{15}$$

where $nx_i = NX_i/Y_i$ denotes the value of net exports relative to the value of output in country i. In deriving condition (15) we use

$$Y_i = s_i H_i + w_i L_i + \Pi_i,$$

which follows from factor market clearing and the definition of profits above. We follow Dekle et. al. (2007) in modeling trade deficits, nx_i, as exogenous parameters.[13]

Equilibrium: An equilibrium of the world economy is a set of prices P_i, $P_i(j)$, $p_i(\omega, j)$; indicator functions $\mathbb{I}_{in}(\omega, j)$; wages w_i, s_i; quantities demanded Q_i, $Q_i(j)$, $q_i(\omega, j)$; quantities produced $y_i(\omega, j)$; and factor demands $l_{in}(\omega, j)$, $h_{in}(\omega, j)$ that satisfy profit maximization, (5) and (14); utility maximization, (1) and (2); goods (11) and factor (12), (13) market clearing conditions; and budget constraints (15), in each country.

Factor mobility: We consider two extreme assumptions regarding internal labor mobility. In one specification we assume that labor is freely mobile within a country across all producers, so that the wage of a given factor is equalized across all producers. This case captures the long run equilibrium. In our alternative specification, we aim to capture the short run, in which workers are tied either to merchandise or services. In this specification we assume that labor is immobile between the set of merchandise sectors and the set of service sectors, but is mobile within the set $j = 1, ..., J_M$ and within the set $j = J_M + 1, ..., J$. In this specification, we take the amount of each factor employed in merchandise and services as fixed and allow skilled and unskilled wages to vary across these aggregate sectors.

2.2 International Trade and the Skill Premium

The two mechanisms linking international trade and the skill premium in our model can be understood as follows. From (14) it follows that the country i firm producing variety (ω, j) with productivity z chooses

$$\frac{h_{in}(\omega, j)}{l_{in}(\omega, j)} = \frac{\alpha_j}{1-\alpha_j} \left(\frac{s_i}{w_i}\right)^{-\rho} z^{\varphi}, \tag{16}$$

where $\varphi = 2(2\phi - 1)(\rho - 1)$.

The parameter α_j shapes the skill intensity of production at the sector level. If $\alpha_{j_2} > \alpha_{j_1}$, then a firm in sector j_2 is more skill intensive than an equally productive firm in sector j_1. As in the Heckscher-Ohlin model, there is a force in our model such that reductions in

[13] To endogenize this parameter, one could, for example, assume that countries have different levels of net foreign assets so that countries with positive net foreign assets run trade deficits. While this would leave our baseline parameterization unaffected—as net foreign assets would have to be chosen to match net exports in the data—solving our counterfactuals would require taking a stand on the details of the determination of asset positions and prices in general equilibrium.

trade costs cause factors to reallocate towards a country's comparative advantage sectors. If country i has a comparative advantage in skill-intensive sectors then this between-sector reallocation will raise its skill premium, and the opposite will occur in a country with a comparative advantage in unskill-intensive sectors. We call this the *Heckscher-Ohlin (H-O) mechanism*.

In practice, firms within a sector may have heterogeneous skill intensities conditional on productivity; i.e., α may vary across varieties ω within a sector j. Under this assumption, the H-O mechanism will be active within sectors; see e.g. Feenstra (2010).[14] In our sensitivity analysis we consider an extended version of the model in which we allow for α to vary within sectors.

The parameter φ, which depends on both ϕ and ρ, shapes the skill bias of technology. We define skill-biased technology following Acemoglu (2009): technology is skill-biased if a higher z increases the marginal product of skilled labor relative to the marginal product of unskilled labor, all else equal. This condition holds in our model if $\varphi > 0$. Hence, we say that technology is *skill biased* if $\varphi > 0$. We say that it is *Hicks neutral* if $\varphi = 0$. If technology is skill biased then more productive firms are more skill intensive within a sector j, whereas if it is Hicks neutral then skill intensity is independent of productivity within a sector. As in other heterogeneous-firm models such as BEJK and Melitz (2003), reductions in trade costs cause factors to reallocate towards exporting and away from domestic firms within a sector, where the exporting firms are, on average, relatively productive in all countries. If technology is skill biased then this within-sector reallocation will tend to raise the skill premium in all countries.[15] We call this the *skill-biased technology mechanism*.

Whereas the H-O mechanism's strength is traditionally understood as depending on countries' relative skill abundance, in our model it is also shaped by θ and by relative $A_i(j)$s. A higher value of θ raises the dispersion of firm-specific productivity draws, z, which tends to raise the importance of differences in z relative to differences in country-sector productivities, $A_i(j)$, and wages, s_i and w_i, in determining the low-cost supplier of a given variety (ω, j). This implies that between-sector comparative advantage is relatively less important for shaping trade patterns. Hence, a higher value of θ reduces the extent of between-sector factor reallocation, and therefore the change in relative wages, in response to

[14] As discussed in the Sensitivity Appendix, if the H-O mechanism is active within sectors and $\varphi = 0$, then within sectors exporting firms are relatively less skill intensive in skill-scarce countries like Mexico, which is counterfactual.

[15] An alternative modeling approach that yields similar qualitative results is to assume instead that trade costs are skill biased; see e.g. Matsuyama (2007). We choose our approach based on the production function (3) because, in the data, larger firms are more skill intensive than less productive firms both within the set of non-exporting firms and within the set of exporting firms. For example, from unpublished Mexican manufacturing plant-level data for 1998 (from the *Encuesta Industrial Anual*) Verhoogen (2008) finds that within industries in Mexico the elasticity of the share of plant workers with tertiary degrees to plant sales is about 0.12 among exporting plants and 0.13 among non-exporting plants.

a trade liberalization. Sector-level productivities $A_i(j)$ also shape the strength of between-sector comparative advantage. For instance, if country i has a comparative advantage in sector j, a higher value of $A_i(j)$ strengthens country i's comparative advantage in this sector. This increases the extent of between-sector factor reallocation. Therefore there is a larger increase (decrease) in the skill premium in skill-abundant (skill-scarce) countries in response to a trade liberalization.

The strength of the skill-biased technology mechanism is shaped by θ and φ. A higher value of θ raises the dispersion of firm-specific productivity draws, which tends to increase the difference between the productivities of exporting firms and domestic firms. This raises the relative difference in skill intensities between these types of firms, and therefore generates a larger increase in the relative demand for skill and the skill premium in response to a trade liberalization. From equation (16), φ is the elasticity of firm skill intensity to firm productivity. A higher value of φ increases the skill intensity of a high productivity firm relative to that of a low productivity firm, so that within-sector factor reallocation from contracting to expanding firms in response to a trade liberalization tends to raise the relative demand for skill and the skill premium more.

We confirm all of the above intuition quantitatively; however, proving these results in the present environment is complicated by the presence of variable markups. In the Online Addendum we set up a perfectly competitive version of the model, based on EK instead of BEJK, in which markups and profit shares do not vary across equilibria. In this environment we provide analytic propositions, under certain simplifying assumptions, that formalize much of the intuition discussed above. We also show in the sensitivity analysis below that our quantitative results are almost identical under Bertrand and under perfect competition. We use the Bertrand model because producer size is uniquely determined, which allows us to link firms in our model to firms in the data.

3 Quantitative implementation

In this section we describe how we parameterize our model. We first describe what features of the data we use to assign values to the model's parameters. We then describe the algorithm that we employ to solve and calibrate the model. Finally, we discuss how our model performs in terms of additional statistics in the data that we do not target in our calibration procedure.

We parameterize a 65-country version of our model, with 64 countries $(n = 1, ..., N-1)$ plus the rest of the world $(n = N)$, where the rest of the world (henceforth ROW) aggregates data from 89 countries. The 64 countries that we include, which are listed in Appendix Table 1, account for approximately 93% of world GDP in our time period. We parameterize the model using data averaged over the years 2005-2007, where possible. We define a skilled worker in the data as one who has completed at least a tertiary degree; merchandise sectors as good producing industries; and service sectors as the remaining sectors, including construction but excluding government, using US Census classifications. This yields 98 merchandise sectors and 155 service sectors. We include 4000 varieties per sector in merchandise and 1000 varieties per sector in services.[16] We use merchandise trade data from Comtrade and abstract from trade in services. Because international trade is a gross output measure (i.e. a fraction of trade takes the form of imports of intermediate inputs for processing and re-exporting as final goods) and our model does not include intermediate goods as an input in production, we target trade volumes relative to gross output in the data. We construct measures of gross output by multiplying value added (which is available for all countries in our data) and the ratio of gross output to value added, separately for merchandise and services. We obtain these ratios from OECD IO tables if available, and we impute them if IO tables are unavailable. All of the output and trade measures that we use are denominated in current US dollars. Details of this procedure are available in the Parameterization Appendix.

3.1 Parameterization

When choosing factor endowments H_n and L_n, we normalize $H_n + L_n = 1$ in all countries. This is without loss of generality, as relative country size is determined jointly by relative country productivities and populations. We must also choose the elasticities of substitution across goods, σ and η, the elasticity between skilled and unskilled workers at the firm level ρ, the elasticity of skill intensity to firm productivity, φ, the dispersion of firm-level productivities, θ, country-specific merchandise shares of absorption, γ_n, country-specific net-exports relative to output, nx_n, sector-level skill intensity parameters, α_j, and trade costs, τ_{in}.

Finally, we must also choose the $J \times N$ country-sector level productivities, $A_n(j)$. Identifying $A_i(j)$ for each country-sector pair directly by estimating productivity is impractical given data availability. Alternatively, we could estimate a sector-level gravity equation in the data and in our model, and choose $A_i(j)$ to match the resulting country fixed effects (see e.g. Levchenko and Zhang 2010). This approach, however, is computationally intensive in our model which does not yield analytic gravity equations. Instead, we use two parsimonious approaches to parameterize $A_n(j)$. These simple parameterizations for $A_n(j)$ impose strong restrictions on our model, but given our target moments we do not think that they significantly affect the impact of trade on the skill premium that we report below. The impact of trade on the skill premium caused by between-sector factor reallocation depends on the extent to which factors reallocate towards or away from skill-intensive sectors on

[16] While services are nontraded, we need to include multiple varieties so that markups do not vary systematically between tradeable and nontradeable industries (which would give rise to additional effects from trade on the skill premium). Our results are not very sensitive to further increases in the number of varieties.

average, rather than the extent to which factors reallocate towards or away from each individual sector. Hence, our approaches to parameterizing $A_n(j)$ aim to capture only the systematic relationship between comparative advantage and skill intensity. Specifically, in both approaches we assume that country-sector productivities satisfy $A_n(j) = T_n \times T_n(j)$, where $T_n(j) = 1$ for all service sectors, $T_n(j) = 1 + (\alpha_j - \overline{\alpha}) t_n$ for merchandise sectors, and $\overline{\alpha}$ is the average skill intensity parameter across sectors. This implies that all service sectors have a common productivity in country n, T_n, whereas sector-level productivity in tradeable sectors in each country is linearly related to skill intensity $(\alpha_j - \overline{\alpha})$. The slope of this relationship is given by t_n, which is country specific. In our baseline approach we choose t_n to match a specific target in each country as described above. In an alternative specification we impose $A_n(j) = T_n$ for all n (i.e. $t_n = 0$).

While we allow H_n, L_n, T_n, t_n, τ_{in}, and γ_n to all vary across countries, we impose that θ, ρ, ϕ, and α_j are all constant across countries because of data availability: for many countries in our sample we do not observe all relevant information that we would require to assign values to these parameters. We show below that in spite of this parsimony, the model does reasonably well where data from a range of countries is available. Given data availability, it would be straightforward to allow for cross-country differences in θ, ρ, ϕ, and α_j.[17]

General parameterization strategy: Our general parameterization strategy is as follows. We group parameters into two categories. The first category includes parameters to which we can directly assign values without having to solve the model: each country's skill endowment ratio, merchandise share of absorption, and net exports relative to output, $H_n/(H_n + L_n)$, γ_n, and nx_n, respectively; the elasticities of substitution across goods, σ and η; and the sector-level skill intensity parameters, α_j. The second category includes parameters that we choose so that endogenous outcomes from the model match salient features of the data: each country's technology parameters, T_n and t_n; trade costs, τ_{in}; the elasticity between skilled and unskilled workers at the firm level, ρ; the elasticity of skill intensity to firm productivity, φ; and the dispersion of firm-level productivities, θ.

Of the parameters in the second category, we choose values for ρ, θ, φ, and t_n (for all n) to match simultaneously a set of moments—one per parameter—we describe in detail below. Our choice for how to choose values for T_n and τ_{in} requires further discussion. Recall that since our model does not yield analytic gravity equations at any level of aggregation we cannot use the approach of Dekle et. al. (2007), which eliminates the need to solve for trade costs or productivities in the original equilibrium. Instead, we must assign values to $N-1$ relative aggregate productivities and $N(N-1)$ trade costs, yielding a total of $(N-1)(N+1) =$

[17] To obtain analytic gravity, the standard approach requires that θ be equal across countries. Since our approach is not based on analytic gravity, we can allow for differences in θ across countries, given data availability.

4224 parameters. We target $N-1$ relative outputs, $Y_i / \sum_n Y_n$, as well as N^2 sales from each origin i to each destination n relative to output, $x_{in} = X_{in} / \left(Y_n^{merch} + Y_i^{merch}\right)$, where Y_n^{merch} denotes merchandise output in country n.[18] In the Parameterization Appendix, we show that of the $N^2 + N - 1$ targets, only $N(N-1)$ are independent. That is, we have $N-1$ more parameters than moments. A related issue has been discussed previously in Waugh (2010).

To deal with this issue we consider two alternative approaches to assigning values to trade costs and productivities. In the first approach, we eliminate parameters by restricting trade costs, as in much of the quantitative trade literature; see e.g. EK, Waugh (2010), and Fieler (2011). Specifically, we eliminate $N-1$ parameters by restricting trade costs to be symmetric for ROW (country N), $\tau_{iN} = \tau_{Ni}$.[19] In the second approach we impose no additional restrictions and we find one, out of potentially many, set of trade costs and productivities that minimizes the distance between model outcomes and our target moments. In our sensitivity analysis we show that these two approaches yield almost identical quantitative implications for the impact of international trade on real wages and the skill premium.[20] In the remainder of the paper, we use the second approach because the solution algorithm converges more quickly.

We now describe our approach in more detail.

Parameters assigned directly without solving the model: We choose a number of parameters directly from data. We choose country skill endowments, $H_n / (H_n + L_n)$, to match the share of workers 25 years and older with a completed tertiary degree (i.e. university graduates with degrees and post-graduates) from the Barro and Lee (2010) dataset for the year 2005.[21] We set α_j to match the share of those employed in sector j with a completed tertiary degree in the US (restricting the sample to only respondents who are employed and currently working), which we obtain from the American Community Survey (ACS) from IPUMS for the years 2005-2007.[22] While we assume the same distribution of

[18] In the Parameterization Appendix, we show that targeting this set of moments is equivalent to targeting a more standard measure, X_{in}/Y_n^{merch}. We use x_{in} rather than X_{in}/Y_n^{merch} because it improves the efficiency of the numerical algorithm.

[19] In our first approach we restrict trade costs in the minimum possible way to equalize the number of moments and parameters. EK, Fieler (2011), and Waugh (2011) follow a related strategy, choosing a simple parameteric form for trade costs that restricts the number of parameters further. In the sensitivity analysis we show that imposing symmetric trade costs in ROW or an alternative country does not affect our results on the impact of trade on real wages and the skill premium.

[20] In the sensitivity analysis we show that we obtain almost identical results even if we restrict all trade costs to be symmetric, $\tau_{in} = \tau_{ni}$ for all i and n.

[21] In the sensitivity analysis, we consider a measure of skill endowment based on the average years of education by country and show that the results remain roughly unchanged conditional on matching our other targets.

[22] Our model implies that factor intensities vary across firms within a sector because of skill-biased technology and heterogeneous productivity. In our baseline specification, the standard deviation of the log share

α_js across all countries, due to lack of data on sector-level skill intensity for many countries, our model endogenously generates differences in sector-level skill intensities across countries. We set nx_n to match the ratio of merchandise net exports relative to total output. We set γ_n to match the merchandise share of absorption using data calculated from the World Bank World Development Indicators, OECD IO tables, and Comtrade (with imputations for those countries not in the OECD IO tables) for the year 2006. Details are available in the Parameterization Appendix. Finally, we set $\sigma = \eta = 2.7$ to match the median 5-digit SITC elasticity of substitution between 1990 and 2001 estimated by Broda and Weinstein (2006).[23]

This leaves the following parameters: T_n, τ_{in}, ρ, θ, φ, and t_n. We parameterize T_n and τ_{in} using the algorithm described in detail below and gross output and trade data described above. We parameterize ρ, θ, φ, and t_n targeting specific moments in the data that we now discuss in detail. Note that we will not target the skill premium level in each country because of lack of comparable data on the skill premium across countries and because our model can match any skill premium level in each country (by extending our production function to allow for an aggregate skill-biased productivity term) while leaving the implications on which we focus essentially unchanged.

First target moment: Our first target moment is the aggregate elasticity of substitution between H and L in the US. Katz and Murphy (1992) estimate that this elasticity is 1.4 whereas Acemoglu and Autor (2010) estimate that it is between 1.6 and 1.8. These authors estimate this elasticity in the US by regressing the change in the log skill premium on the change in the log of college educated workers relative to non-college educated workers and a time trend that captures changes in relative factor demands. We target a value for this elasticity of 1.6. To calculate this aggregate elasticity in our model, we feed in a one-time, exogenous change in the stock of skilled labor in the US in our baseline parameterization and calculate $\Delta \left[\log \left(\frac{H_{US}}{L_{US}} \right) \Big/ \log \left(\frac{w_{US}}{s_{US}} \right) \right]$. Note that if $\varphi = 0$ and there is only one sector, then ρ, the elasticity of substitution between skilled and unskilled labor at the firm level, equals the aggregate elasticity in our model; in this case, we would have $\rho = 1.6$. With $\varphi > 0$ and many sectors, ρ and the aggregate elasticity are still tightly linked. We obtain a value of $\rho = 1.4$; the labor reallocation to skill-intensive firms and sectors produces a smaller decrease in the skill premium for the same increase in H/L.

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of skilled workers across firms for the median sector in the US is about 0.1 and is similar across countries (the standard deviation across sectors in the US is 0.5). As we discussed in section 2.2, in practice firms with the same z within a sector may also have heterogeneous skill intensities, so that the H-O mechanism is active within sectors. In our sensitivity analysis we consider a version of the model in which we allow for α to vary within sectors.

[23] In our baseline specification we set $\sigma = \eta$ to avoid taking a stand on the relationship between average skill intensity in production and substitutability in demand. In the sensitivity analysis we consider lower values of the elasticity of substitution across sectors within merchandise and services, σ.

Second target moment: Our second target moment is the aggregate elasticity of trade with respect to variable trade costs. There is a large literature estimating this elasticity. EK's preferred estimate is 8.28, but more recent estimates place this elasticity significantly lower. For example, Donaldson's (2010) preferred estimate is 4, Simonovska and Waugh (2011) estimate a value between 2.47 and 5.51, Eaton et. al.'s (2011) preferred estimate is 5, and Costinot et. al.'s (Forthcoming) preferred estimate is 6.53. We target a value of 5. To determine the value of this elasticity in our model, we regress the log of exports from i to n on an importer fixed effect, an exporter fixed effect, and on the log of the trade cost from i to n, τ_{in}, which we observe in the model. Note that if $\varphi = 0$, then θ, the dispersion of firm-level productivities, equals the inverse of the aggregate trade elasticity in our model; in this case, we would have $\theta = 0.2$. With $\varphi > 0$, θ and the aggregate trade elasticity are still tightly linked. We obtain a value of $\theta = 0.25$. In our sensitivity analysis we show that we obtain essentially the same value for θ in our alternative approach to assigning values to trade costs and productivities. This is perhaps not surprising given the result that if $\varphi = 0$, then θ equals the inverse of the aggregate trade elasticity in our model, in all of our parameterizations.[24]

Third target moment: Our third target moment is the elasticity of plant skill intensity—measured as the share of workers in any given plant with a tertiary degree—to plant sales, controlling for sector, in Mexican manufacturing,

$$\log\left[\frac{h_i}{h_i + l_i}\right] = \psi_0 + \psi_1 \log Sales_i + SectorFE_i + \varepsilon_i, \tag{17}$$

where $h_i / (h_i + l_i)$ is the share of the workforce in plant i that has completed a tertiary degree, $Sales_i$ is plant i sales, and $SectorFE_i$ is a sector fixed effect. From unpublished Mexican manufacturing plant-level data for 1998 (from the *Encuesta Industrial Anual*, which excludes maquiladoras), Verhoogen (2004, 2008) estimates this elasticity to be $\psi_1 = 0.136$. To determine the value of this elasticity in our model, we estimate equation (17) using artificial data from Mexican merchandise firms. Note that in our model if $\varphi = 0$ then $\psi_1 = 0$, and if $\varphi > 0$ then $\psi_1 > 0$. More generally, this elasticity is strictly increasing in φ, as we demonstrate in Table 1, in which we vary φ (by varying ϕ) while holding θ and ρ fixed at their levels in the baseline parameterization:

φ	0	0.08	0.24	0.4	0.64	0.72
Elasticity	0	0.05	0.085	0.139	0.213	0.23

Table 1: φ and the elasticity of firm skill intensity to firm sales in the model

[24] Below we argue that we would obtain a similar value of θ if we targeted features of the US firm-size distribution, as in BEJK.

We obtain a value of $\varphi = 0.4$; given $\rho = 1.4$, this implies $\phi = 0.75$.

Fourth target moment: Our fourth and final target moment aims to capture each country's comparative advantage across sectors. Our goal is to match the extent to which each country's net exports, normalized by total trade in that sector, are greater in skill-intensive or unskill-intensive sectors. Specifically, we regress the ratio of country n's net exports in sector j to the sum of exports from n plus imports into n in sector j on a constant and the share of workers in sector j with a tertiary degree in the US, measured from the ACS:

$$\frac{\sum_i \left[X_{ni}(j) - X_{in}(j)\right]}{\sum_i \left[X_{in}(j) + X_{ni}(j)\right]} = \beta_{0n} + \beta_n \frac{H_{US}(j)}{H_{US}(j) + L_{US}(j)} + \varepsilon_n(j).$$

For the rest of the world ($n = N$), we assume β_N equals the median value of β_n for $n < N$. A positive value of β_n (e.g. $\beta_{US} = 0.55$) implies that a country tends to have relatively higher net exports in skill-intensive sectors, while a negative value of β_n (e.g. $\beta_{CHN} = -1.30$) implies that a country tends to have relatively higher net exports in unskill-intensive sectors. The upper panel of Figure 1 plots each country's $\beta_n - \overline{\beta}$ against its skill abundance in the data, where $\overline{\beta}$ is the average of β_n across countries weighted by merchandise output, $\overline{\beta} = \sum_i \frac{Y_i^{merch}}{\sum_n Y_n^{merch}} \beta_i$, and where Y_i^{merch} denotes merchandise gross output in country i. Note that β_n and skill abundance are positively correlated, which implies that skill-abundant countries tend to have higher net exports in skill-intensive sectors.

Whether a country in our model has a comparative advantage in skill-intensive or unskill-intensive sectors is determined by its factor endowments and the slope of its sectoral productivities $T_n(j)$ in merchandise sectors, t_n, relative to its trading partners. While we take skill endowments directly from data, we have two alternative ways to choose the slope of sectoral productivities. In our baseline approach we choose sectoral productivities to match our fourth moment, $\beta_n - \overline{\beta}$, in each country, whereas in our alternative approach we simply set $t_n = 0$ for all countries.

Specifically, in our baseline parameterization we choose t_n in each country to match the regression coefficients $\beta_n - \overline{\beta}$ in the model and in the data (that is, we match every point in the upper panel of Figure 1). We pick the combination of t_n's such that the "average" country has a constant $A_n(j)$ across sectors; i.e. $\sum_i \frac{Y_i^{merch}}{\sum_n Y_n^{merch}} t_i = 0$. We choose to normalize the weighted average t_n to zero because comparative advantage is determined by *relative* t_ns (i.e. there are many different combinations of t_n's that allow us to match the β_n coefficients in the data).

We also consider an alternative parameterization in our sensitivity analysis in which we do not target this fourth moment, but instead fix $t_n = 0$ for all countries. That is, we assume that $A_n(j)$ is constant across all sectors, both in merchandise and services. This approach is consistent with empirical evidence in Morrow (2010) that countries do not have

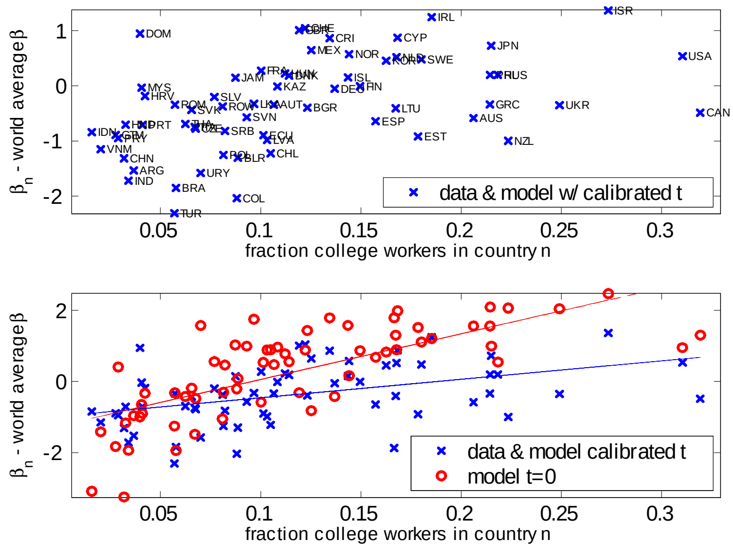

Figure 1: Comparative advantage and skill abundance.

systematically higher or lower relative productivities in sectors in which they have a factor-endowment based comparative advantage. The lower panel of Figure 1 includes the values of $\beta_n - \overline{\beta}$ that we obtain in this alternative parameterization. Note that with $t_n = 0$, the relation between $\beta_n - \overline{\beta}$ and skill abundance is significantly stronger than in the data. This is highlighted by the two regression lines in the lower panel. Moreover, in the Sensitivity Appendix we also fully re-parameterize all t_ns in the specification of the model in which the H-O mechanism is active within sectors (where we assume that αs are heterogeneous within sectors).

3.2 Solution algorithm

Our solution algorithm involves three loops: an outer loop, a middle loop, and an inner loop. In the outer loop we iterate over ϕ, θ, and ρ to match our first three targets described above. In the middle loop, we iterate over τ_{in}, T_n, and t_n to match bilateral export volumes, relative country sizes, and the extent of each country's comparative advantage across sectors (target 4). The middle loop differs from the literature in that it allows us to match bilateral trade flows without analytic gravity equations at any level of aggregation. In the inner loop we iterate over w_n, s_n, and the aggregate profit share $\pi_n = \Pi_n / (w_n L_n + s_n H_n)$ to solve for the equilibrium of our model. This loop builds upon Alvarez and Lucas (2007), extending their approach in four respects: we have (i) no analytic gravity equations, (ii) two factors, (iii) positive profits, and (iv) non-balanced trade. However, unlike Alvarez and Lucas (2007), we only demonstrate existence numerically. We have not found any indications of multiple equilibria in our numerical work. In what follows we describe the solution algorithm in the specification with full labor mobility. Details of the middle and inner loop are provided in the Parameterization Appendix.

Inner loop: In the inner loop, we take the values of ϕ, θ, ρ, τ_{in}, T_n, and t_n as given and iterate over w_n, s_n, π_n for each country. In the inner loop, we guess wages and profits and, given these guesses, solve for the model's implied factor demands and net exports for each country. We then construct excess relative demand for skill and excess net exports for each country and use these to iterate on our guess in a similar fashion to Alvarez and Lucas (2007). If excess relative demand for skill is positive in country n, we raise its skill premium, which reduces its relative demand for skill. Similarly, if net exports constructed from sourcing outcomes for each good in each market are higher than net exports calculated from the income side (using our guesses for wages, profit shares, and the ratio of net exports to output observed in the data) in country n, we raise both wages in country n (for a given skill premium), which reduces the set of domestically produced goods and increases the set of imported goods.

Middle loop: In the middle loop we take the values of φ, θ, and ρ as given and iterate over τ_{ni}, T_n, and t_n. We guess τ_{ni}, T_n, and t_n, and, given these guesses construct in the model (i) the ratio of exports from n to i relative to the sum of merchandise outputs in countries n and i, $x_{ni}^m = X_{ni}^m / \left(Y_i^{merch} + Y_n^{merch}\right)^m$, (ii) the ratio of each country's output relative to world output, $Y_n^m / \sum_i Y_i^m$, and (iii) the regression coefficient determining the extent to which country n is net exporter in skill-intensive sectors from target moment 4, $\beta_n^m - \overline{\beta}^m$. We target $X_{in} / \left(Y_n^{merch} + Y_i^{merch}\right)$ and relative outputs rather than X_{in}/Y_n^{merch} because it significantly improves the efficiency of the numerical algorithm. By comparing $(i) - (iii)$ to the value of those variables in the data, we iterate over τ_{ni}, T_n and t_n as follows. If the ratio of exports from n to i relative to the sum of merchandise outputs is higher in the model than in the data, we raise τ_{ni}. If the ratio of country n's output relative to world output is higher in the model than in the data, we lower T_n. Finally, if country n's net exports in skill-intensive relative to unskill-intensive sectors is higher in the model than in the data, we lower t_n.

In this step of our algorithm, we choose not to match trade volumes that are sufficiently small. Specifically, we set $\tau_{in} = \infty$ if the ratio of country i's exports to country n relative to the sum of country i's and country n's outputs is less than 10^{-6} in the data; this eliminates 123 bilateral trade costs out of a total of 4160.

Outer loop: In the outer loop we iterate over θ, ρ, ϕ to match target moments 1, 2, and 3. We raise ρ if the model's implied aggregate elasticity of substitution between skilled and unskilled workers in the US is too low relative to target 1, we raise θ if the model's implied

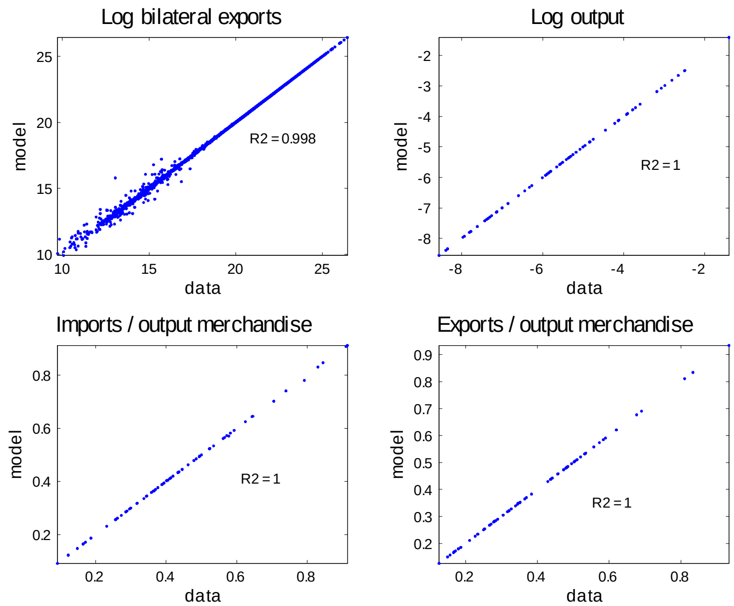

Figure 2: Fit of the model relative to the data.

elasticity of trade with respect to trade costs is too high relative to target 2, and we raise ϕ if the model's implied elasticity of plant skill intensity to plant sales is too low relative to target 3.

3.3 Targeted and additional moments

In this section we discuss the fit of the model relative to the data both for the moments that we targeted as well as a range of moments that we do not explicitly target.

Targeted moments: Here we discuss the model's fit relative to the data for the moments that we target in the middle loop. We report the remaining moments in the Parameterization Appendix.

Figure 2 plots the model's fit relative to the data in four respects. In the upper left quadrant we plot log bilateral exports in the data and in the model for all origin-destination pairs for which the model does not imply zero trade; the model implies zero trade for the 123 of the possible 4160 origin-destination pairs for which we set $\tau_{in} = \infty$ (which account for 0.0001% of total world trade between our 65 countries) and for an additional 31 origin-destination pairs (which account for 0.047% of total world trade between our 65 countries).[25] Note that most points are on or very near the diagonal, especially for large trade flows. The R^2 of the regression of $\log\left(X_{in}^d\right)$ on $\log\left(X_{in}^m\right)$ is 0.998. In the upper right quadrant we plot

[25] Similar to Eaton, Kortum, and Sotelo (2011), our model with a discrete number of varieties can generate zero bilateral exports even with finite trade costs.

log output in the data and in the model. All points are on or very close to the diagonal and the R^2 of the regression of $\log\left(Y_i^d\right)$ on $\log\left(Y_i^m\right)$ is 1. In the bottom left (right) quadrant we plot imports/output (exports/output) in merchandise in the data and in the model. Again, all points lie on or close to the diagonal and the R^2s of the relevant regressions are both 1.

Standard gravity models imply a constant elasticity of trade flows with respect to variable trade costs. Specifically, $\log\left[X_{in}X_{ni}/\left(X_{ii}X_{nn}\right)\right]$ is linearly related to $\log\left(\tau_{in}\tau_{ni}\right)$, with a slope equal to the constant elasticity of trade flows with respect to variable trade costs. How well does this relationship hold in our model, which does not yield this relationship analytically? Figure 3 plots $\log\left[X_{in}X_{ni}/\left(X_{ii}X_{nn}\right)\right]$ and $\log\left(\tau_{in}\tau_{ni}\right)$ and reports the coefficient from a linear regression both with $\varphi = 0$, in which case our model yields analytic gravity, and in our baseline specification in which we do not obtain analytic gravity. Whereas the slope exactly equals the elasticity if $\varphi = 0$, the difference between the slope and the trade elasticity is still small in our baseline parameterization. Note that both panels in Figure 3 feature some degree of dispersion (more so with skill-biased technology) due to randomness arising from the finite number of varieties.

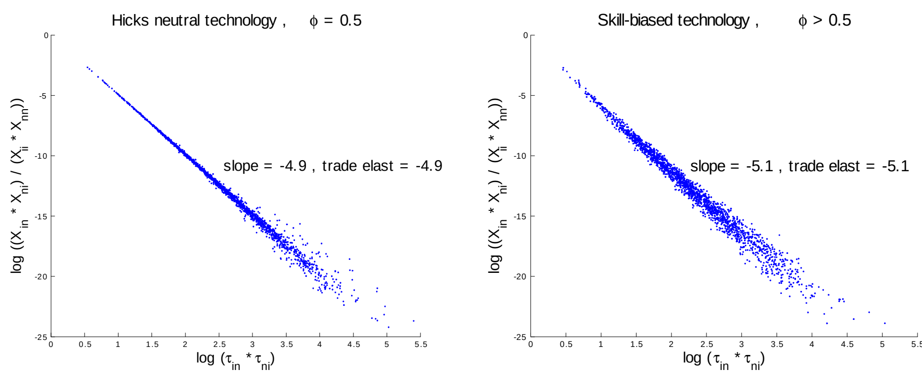

Figure 3: Relationship between bilateral trade costs and bilateral exports in the model.

Since we not only match log bilateral exports but also back out the model's implied trade costs, τ_{in}, we can project trade costs onto standard "gravity" variables to see if the trade costs have the expected relationship with observables. We project trade costs onto distance, distance^2, an indicator for common language, an indicator for common border, exporter fixed effects, and importer fixed effects, excluding ROW for which common language and border are not well defined. The R^2 of this regression is 0.74 and all the variables—distance, distance^2, common language, common border—have the expected signs and are highly statistically significant.

We can also use the inferred τ_{in}s to ask whether poor countries tend to face higher export and/or import costs, conditioning on other observables. To address this question, we regress importer (exporter) fixed effects from the previous regression on importer (exporter) GDP per capita (PPP adjusted). We find that the coefficient on importer GDP per capita is negative and highly statistically significant while the coefficient on exporter GDP per capita is negative and significant at the 10% level. This suggests that poor countries suffer from higher import and higher export costs, all else equal.[26]

Other within-sector moments not targeted: Whereas in parameterizing the model we target the elasticity of plant skill intensity to plant sales (controlling for sector) using Mexican manufacturing data, we can also compare our model's predictions to the data along a different dimension. We first calculate the exporter skill-intensity premium controlling for sector by running the following regression at the plant level,

$$\ln\left[\frac{h_i}{h_i+l_i}\right] = \psi_0 + \psi_1 Exporter_i + SectorFE_i + \varepsilon_i,$$

in both the model and the data, where $h_i/\left(h_i+l_i\right)$ is the share of the workforce in plant i that has completed a tertiary degree, $Exporter_i$ is a plant-level exporter dummy variable, and $SectorFE_i$ is a sector fixed effect. Using data generated by the model we find that $\psi_1 = 0.25$ for Mexican merchandise firms. From unpublished Mexican manufacturing plant-level data for 1998, Verhoogen (2008) estimates $\psi_1 = 0.21$. Hence, by matching moment 3 using Mexican data our model also does reasonably well in matching the exporter skill intensity premium in Mexico.

Our model yields predictions for all countries, not only for Mexico. Menezes-Filho et. al. (2008) has data, from the 1995 *Pesquisa Industrial Anual* survey of large manufacturing firms, on Brazilian firms and their skill intensity. Hence, we calculate moment 3—the elasticity of firm skill intensity to firm sales controlling for sector—for Brazilian firms. Using data generated by the model we obtain $\psi_1 = 0.24$ for Brazilian merchandise firms. In unpublished results Menezes-Filho et. al. (2008) estimate $\psi_1 = 0.36$. We also calculate a variation of moment 3, the elasticity of firm skill intensity to domestic sales (as opposed to total sales) controlling for sector,

$$\log\left[\frac{h_i}{h_i+l_i}\right] = \psi_0 + \psi_1 \log\left(Domestic\ sales\right)_i + SectorFE_i + \varepsilon_i.$$

Using data generated by the model we obtain $\psi_1 = 0.34$ for Brazilian merchandise firms. In unpublished results Menezes-Filho et. al. (2008) estimate $\psi_1 = 0.34$. Therefore, although we parameterize φ using Mexican data, our model does reasonably well in accounting for

[26] We find very similar results—both regressing trade costs on gravity variables and regressing fixed effects on GDP per capita—in our alternative solution algorithm in which we impose that ROW (and, alternatively the US) faces symmetric trade costs, so that the number of parameters equals the number of target moments. Although it is tempting to relate our results on relative trade costs for poor and rich countries to Waugh (2010), our parameterization includes a smaller number of countries and differs along a range of dimensions.

the relationship between firm-level skill intensity and firm-level outcomes in Brazil as well. Moreover, the model predicts correctly that the elasticity of firm skill intensity to firm sales is higher in Brazil than in Mexico.

We can also compare our model's predictions for US firms with US data. The model over-predicts the share of US merchandise firms that export, which is 51% in the model. Bernard et. al. (2007b) report that the fraction of exporting firms in US tradable goods industries and manufacturing in 2002 was 15% and 18%, respectively. This overstatement of the fraction of exporters is similar to that found in BEJK. Matching the data on this margin would require incorporating a fixed cost of exporting into the model. However, the model does well in predicting the share of exporters' revenues in total merchandise revenues. In the model, this share is 65% in the US, whereas from BEJK it can be inferred that it is 60% for US plants in manufacturing (using the 1992 Census of Manufactures).[27] Similarly, the model does well in predicting the exporter premium for value added per worker in the US. Specifically, if we regress the log of value added per worker on an export status indicator and a sector fixed effect in US merchandise firm-level data generated by the model, we obtain an exporter premium of 0.135 log points,[28]

$$\log\left(VA \text{ per worker}_i\right) = \psi_0 + \psi_1 Exporter_i + SectorFE_i + \varepsilon_i.$$

Bernard et. al. (2007b) run the same regression on US manufacturing firm-level data from the 2002 Census of Manufactures and obtain an exporter premium of 0.11. Finally, we can also calculate moment 3 in the US. Using data generated by our model, we obtain an elasticity of plant skill intensity to plant sales (controlling for sector) of 0.14 for US merchandise firms. Bernard et. al. (2007b) run the same regression for US manufacturing firms using the 2002 Census of Manufactures and obtain an elasticity of 0.11. Unfortunately, Bernard et. al. (2007b) do not have access to our measure of skill intensity—they use the share of non-production workers rather than the share of workers in the firm with a tertiary degree—so the data and model-based elasticities are not as comparable as the Mexican and Brazilian elasticities.

In summary, although we parameterize φ using Mexican data, our model does reasonably well in accounting for a range of facts that we did not target in Mexico, Brazil, and the US—

[27] In particular, BEJK report, using the 1992 Census of Manufactures, that the average exporting plant's sales is 5.6 times larger than those of the average non-exporting plant, and 21% of plants are exporters. From these two observations, it follows that the share of exporters revenues in total revenues is equal to $\left([5.6 * (0.21/0.79)]^{-1} + 1\right)^{-1} = 0.598$.

[28] This variation in value added per worker stems mostly from differences in markups across producers, as in BEJK (and not from variation in skill intensity across producers within sectors). With perfect competition, the difference in value added per worker between exporters and non-exporters in the US is positive but close to zero.

three countries for which we have data that can be compared with data generated by the model. Of course, it remains an open question to what extent our parameterized model is consistent with the relationship between firm size and skill intensity in other countries for which we do not have available data.

Other between-sector moments not targeted: Using US trade and production data we also regress normalized trade (the ratio of exports plus imports to absorption) in merchandise sector j in the US on sector j's skill intensity in the US, both using the BEA's detailed IO tables for the 2002 Benchmark and using data generated by the model,

$$\frac{\sum_n \left[X_{USn}(j) + X_{nUS}(j)\right]}{P_{US}(j)\, Q_{US}(j)} = \psi_0 + \psi_1 \frac{H_{US}(j)}{H_{US}(j) + L_{US}(j)} + \varepsilon_j.$$

Using data generated by the model we obtain $\psi_1 = 0.88$ whereas using data from the BEA we obtain $\psi_1 = 0.70$, which is significant at the 1% level.

This prediction arises in our model from the interaction between skill-biased technology and skill-intensity variation across sectors. To see this, we fully re-parameterize the model imposing $\phi = 0.5$ and find, using data generated by the model for the US in this alternative parameterization, that $\psi_1 = -0.06$. The interaction between skill-biased technology and skill-intensity variation across sectors implies that differences in firm productivities, zs, are relatively more important in shaping unit costs of production in skill-intensive sectors. Intuitively, if productivity is skill biased, then differences in productivities are relatively more important in sectors in which skilled labor is relatively more important. Specifically, using equation (4) we can show that unit costs are more sensitive to firm productivity z the higher is α_j if and only if $\phi > 1/2$,

$$\frac{d}{d\alpha_j}\left|\frac{d\log c_{ink}(\omega, j)}{d\log z}\right| > 0 \Leftrightarrow \phi > 1/2. \tag{18}$$

Hence, if $\phi > 1/2$—as it is in our parameterization—then the distribution of unit costs is more dispersed in more skill-intensive sectors, in spite of the fact that the distribution of productivities is the same across sectors.[29] Condition (18) implies that our model predicts a positive relationship between normalized trade in sector j and sector j's skill intensity. The intuition for this result is exactly the same as the intuition for why there is more trade in Ricardian models the higher is the dispersion of productivities, θ; see e.g. EK and Fieler (2011). This result generates a set of additional predictions that we discuss in section 5.

[29] In spite of differences in the dispersion of unit costs between sectors, we find quantitatively that trade elasticities do not differ much across sectors.

4 Counterfactuals

We use the parameterized model to conduct a series of counterfactuals in which we vary trade costs. First, we consider a change in trade costs such that countries move from autarky to the baseline parameterization. Second, we reduce trade costs 10% from the baseline parameterization. In this section we focus on the implications of our counterfactual exercises for real wages and the skill premium. Across all of our counterfactual exercises we find a consistent set of qualitative results. The real wage rises for both factors of production in almost all countries. However, the real wage of skilled labor rises significantly more than unskilled labor, since the skill premium rises in almost all countries. In section 5 we will also show that there is more within- than between-sector factor reallocation, as found in Haltiwanger et. al. (2004); and that the relative price of skill-intensive goods falls, as found in Lawrence and Slaughter (1993). We also consider in this section two additional counterfactuals to study the implications of growth in China's TFP and skill abundance on the skill premium of its trading partners.

4.1 Autarky to Baseline Parameterization

We consider a reduction in trade costs, moving each country from autarky to the baseline parameterization, with full labor mobility between merchandise and service sectors.

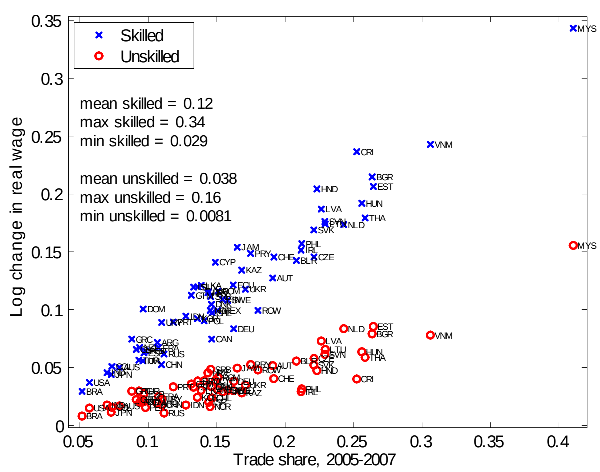

Figure 4: Log changes in real wages for skilled and unskilled labor against the aggregate trade share, resulting from moving from autarky to the baseline parameterization with full labor mobility.

Figure 4 shows the log change in the real wage in the baseline parameterization relative to autarky (henceforth, the log change in the real wage) for skilled and unskilled labor plotted against the aggregate trade share (the average of exports and imports relative to total output) for each country. Note that the real wage rises for both skilled and unskilled workers in all countries. As in standard quantitative trade models, real wage gains of moving away from autarky are rising in trades shares; see e.g. Arkolakis et. al. (2012).[30]

Figure 4 also highlights that the gains from trade liberalization are very unevenly distributed within countries in our model. For instance, whereas a skilled worker's real wage rises by 23% in Costa Rica, an unskilled worker's real wage rises by only 4%. The ratio of the change in a skilled worker's real wage relative to the change in an unskilled worker's real wage, $\Delta \log (s_n/P_n) / \Delta \log (w_n/P_n)$, is 3.1 for the median country. This ratio can be expressed as one plus the log change in the skill premium normalized by the change in the real wage of unskilled workers,

$$\frac{\Delta \log (s_n/P_n)}{\Delta \log (w_n/P_n)} = 1 + \frac{\Delta \log (s_n/w_n)}{\Delta \log (w_n/P_n)}.$$

Figure 5 plots the log change in the skill premium, $\Delta \log (s_n/w_n)$, against the aggregate trade share in the baseline for each country (i.e. the distance between the red and blue points in the figure above).

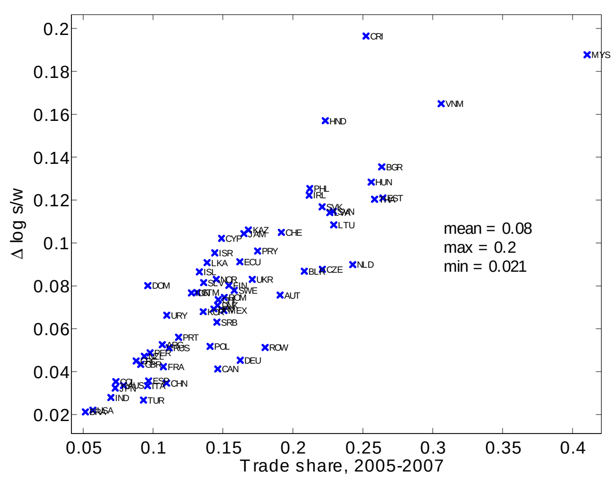

Figure 5: Log changes in skill premia against aggregate trade shares resulting from a move from autarky to the baseline parameterization with full labor mobility.

The skill premium rises in all countries, by 8% on average, but the effect varies widely across countries in our sample. The skill premium rises by as much as 20% in Costa Rica and Malaysia and by as little as 2% in the US and Brazil. Note that while changes in skill premia are small in some countries (to a large extent because trade shares are small), they

[30] In our model, the change in the real wage of the representative consumer—preferences are homothetic—differs from the change in welfare because profits and net exports are not zero.

are large relative to changes in real wages; i.e., $\Delta \log (s_n/w_n) / \Delta \log (w_n/P_n) = 1.5$ in the US.

There are two sources of variation in the data that help explain the dispersion across countries in the impact of trade on the skill premium predicted by our model. Changes in the skill premium are positively correlated with changes in trade shares across countries (the correlation is 0.88) and negatively correlated with country size (the correlation is -0.62). The skill premium changes more moving from autarky to the baseline in a country with a higher trade share because factor reallocation is greater there, and in a smaller country because factors reallocate only towards the very productive, skill-intensive firms there; to see this, note that for a fixed trade share, reducing T_n requires higher variable trade costs, which increases the difference in the average productivity and, hence, the skill-intensity of exporters to non-exporters. While a country's gross output and its trade share are negatively correlated, both matter independently. To see this, we regress the change in a country's skill premium on its gross output and its trade share and find that both coefficients are significant.

On the other hand, a country's skill abundance, $H_n/(H_n + L_n)$, is essentially uncorrelated with its change in the skill premium in this exercise (the correlation is -0.16). This is because our model predicts that the skill premium rises not only in skill-abundant countries like the US, but also in skill-scarce countries such as China and Honduras. The H-O mechanism is not particularly important for shaping the impact of trade on the skill premium in our parameterization for two reasons. First, the skill-biased technology mechanism is stronger than the H-O mechanism. Second, the H-O mechanism is weak.

To understand why the H-O effect is weak we consider three variations of our baseline parameterization in which we impose $\varphi = 0$, so that the skill-biased technology mechanism is inactive. In the first variant, displayed in the first column in Figure 6, we re-parameterize the model to match all targets except for the third target moment (this requires $\theta = 0.2$ to match the trade elasticity of 5). The correlation between changes in the skill premium and skill abundance rises from to -0.16 to 0.25 and the skill premium falls in 35 out of out 65 countries. However, the strength of the H-O mechanism is still weak. For instance, the maximum and minimum changes in the skill premium are $+2.7\%$ and -2.6%, respectively. In the second variant, displayed in the second column in Figure 6, we additionally do not match the extent of between-sector trade (target moment 4) and instead set $t_n = 0$. This gives rise to excess between-sector trade in the model—the correlation between β_n and $H_n/(H_n + L_n)$, displayed in Figure 6, is too high relative to the data—and the H-O mechanism becomes stronger. The correlation between changes in the skill premium and skill abundance rises from to 0.25 to 0.53. Finally, in the third variant displayed in the third column in Figure 6, we additionally lower the dispersion of productivities across firms, setting $\theta = 0.1$ (which implies a trade elasticity close to 10). This is closer to the standard H-O model, which abstracts from firm heterogeneity. This variant gives rise to even more between-sector trade, implying that the H-O mechanism becomes stronger again.

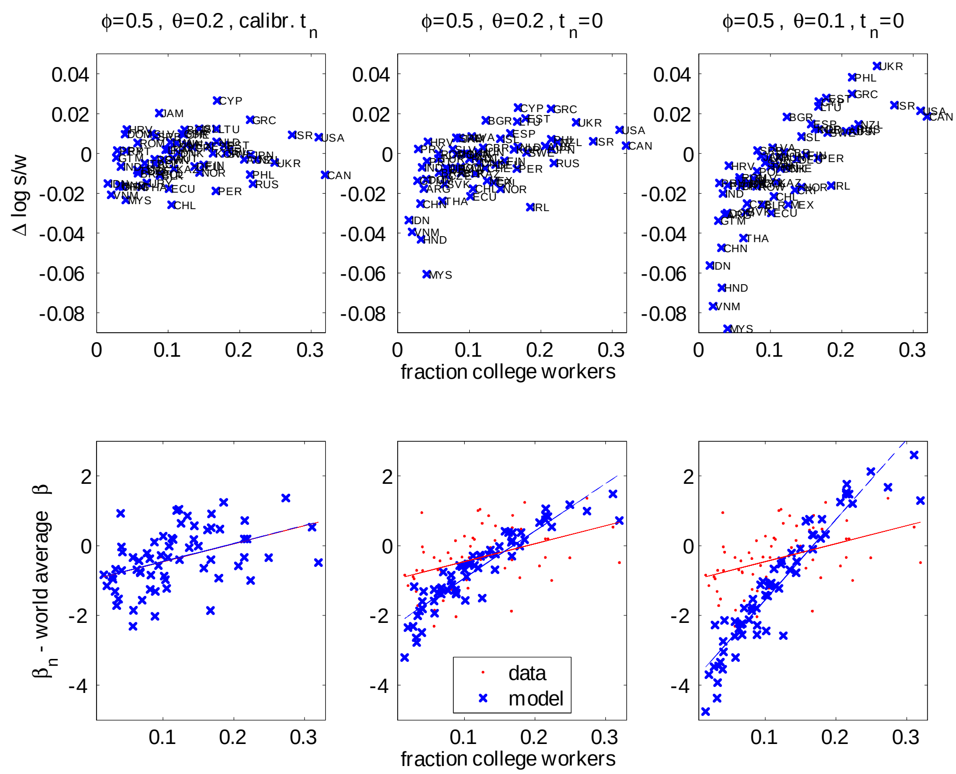

Figure 6: Alternative parameterizations to understand why the H-O mechanism is weak.

The correlation between skill abundance and changes in the skill premium rises to 0.77. The maximum and minimum changes in the skill premium are now 4.4% and -8.8% in skill-abundant and skill-scarce countries, respectively. We conclude from this analysis that the H-O mechanism is weak in our baseline parameterization because we match the elasticity of trade with respect to variable trade costs (so that firm productivity dispersion is high) and because we match the extent of between-sector trade (constraining the amount of between-sector factor reallocation), as discussed in section 2.2.

4.2 Ten Percent Reduction in Trade Costs

We now consider a simultaneous 10% reduction in all bilateral trade costs, starting from the baseline parameterization; that is, $\tau'_{in} = \tau_{in}/1.1$ for all $i \neq n$ (since $\tau_{in} > 1.1$ for all $i \neq n$). In the counterfactual equilibrium we assume that net exports relative to total output, nx_n, remains at the same level as in our baseline parameterization for each country except ROW (net exports in ROW are chosen as a residual, such that there is balanced trade at the world level). We perform this counterfactual both with full mobility (to capture the long-run effects) and limited mobility (to capture the short-run effects). In the case of limited mobility, in which we fix the stock of skilled and unskilled labor in the merchandise and service sectors at their baseline level, we report the change in the skill premium in merchandise sectors; the skill premium is roughly unchanged in service sectors.

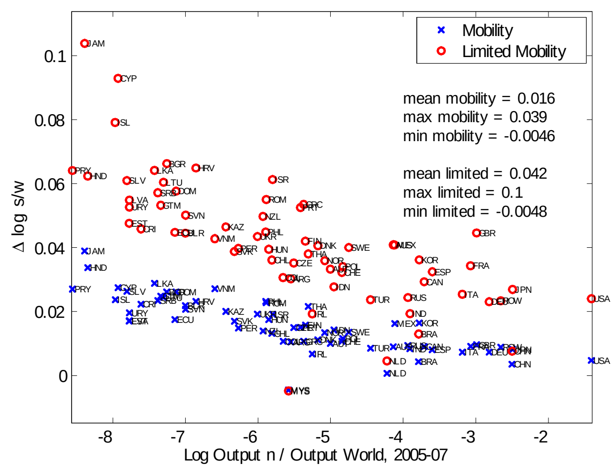

Figure 7: Log change in the skill premium against country output—relative to world output—for each country, both with full and limited factor mobility, resulting from a 10% reduction in trade costs.

The real wage rises for skilled and unskilled workers in all countries with full mobility, and it falls for unskilled workers in only two of our 65 countries (Cyprus and Greece) with limited mobility. As in the previous counterfactual exercise, the gains for workers who have completed tertiary degrees are substantially larger than for those who have not. Specifically, the ratio of the change in a skilled worker's real wage relative to the change in an unskilled worker's real wage for the median country is 3.5 with limited mobility and is 1.9 with full mobility.

Figure 7 plots the log change in the skill premium against country output—relative to world output—for each country, both with full and limited factor mobility; we display relative country size on the x-axis—instead of trade shares as in the previous figures—because output has more explanatory power. Changes in the skill premium with limited mobility are roughly three times larger than those with full mobility. The mean rise in the skill premium is 4.2% with limited mobility and 1.6% with full mobility. We find that the skill premium rises in almost all countries, but the effect varies widely across countries in our sample. For example, the skill premium rises by as much as 10% (4%) in Jamaica with limited (full) factor mobility.[31]

[31] To assess the maximum effects from further reductions in trade costs, we consider an extreme counter-

4.3 Growth in China

We now consider two experiments aimed at capturing the implications of structural transformation in China for the skill premium of its trading partners.[32] In particular, we consider a large rise in China's TFP and its skill abundance. In both of these counterfactual equilibria we assume that net exports relative to total output, nx_n, remains at the same level as in our baseline parameterization for all countries except ROW (net exports in ROW are chosen as a residual, such that there is balanced trade at the world level).

The left panel of Figure 8 plots the log change in the skill premium in the other 64 countries that results from a three-fold rise in Chinese TFP, both with full and limited factor mobility. As China becomes a larger country in the world economy (the share of China in world output increases from 8.2% in our baseline parameterization to 19.3% under this counterfactual), trade with China relative to output rises in all countries. Given that China is a relatively skill-scarce country, both the H-O and the skill-biased technology mechanisms increase the skill premium in all countries. This is especially true for those countries that trade the most with China, such as Vietnam, Malaysia, and the Philippines. The effects are small in countries like the US for which trade with China relative to output, both measured in US dollars, is small.

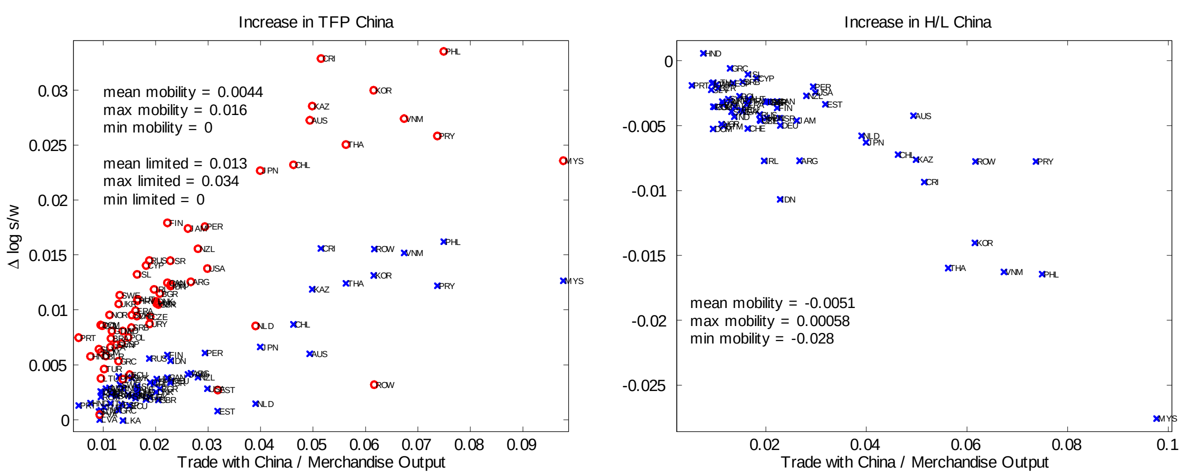

Figure 8: The impact of an increase in China's TFP (in the left panel) and China's skill abundance (in the right panel).

The right panel of Figure 8 plots the log change in the skill premium in the other

factual in which we set all bilateral trade costs equal to 1. The maximum, minimum, and mean change in the skill premium with limited (full) mobility are 41.3% (19.2%), 0.7% (-0.2%), and 19.3% (7.74%), respectively.

[32] Bloom et. al. (2011) documents that rising Chinese imports reallocated employment towards more innovative and technologically advanced firms within Europe.

64 countries resulting from an increase in China's skill abundance, from its current level, $H_{Chn}/\left(H_{Chn}+L_{Chn}\right)=0.03$ to the level in the US, $H_{US}/\left(H_{US}+L_{US}\right)=0.31$. In this counterfactual, given that we feed in changes in factor endowments, we only consider the case with full factor mobility between sectors. As China becomes more skill abundant, the H-O mechanism causes the skill premium to fall in almost all countries, and it falls most for those countries with the highest trade shares with China: e.g. Vietnam, Malaysia, and the Philippines.

4.4 Sensitivity

In the Sensitivity Appendix we conduct a range of sensitivity analyses focusing on the counterfactual in which we move each country from autarky to the baseline parameterization. We quantitatively confirm our qualitative insights, from section 2.2, that the impact of trade liberalization on the skill premium is increasing in both the dispersion of productivities across firms, θ, and the elasticity of skill intensity to firm productivity, φ. We show how changing the elasticity of substitution across sectors within merchandise and services, σ, affects the impact of trade on the skill premium. A lower value of σ reduces the impact of trade on s_n/w_n, because trade liberalization induces less between-sector reallocation. We show that our results are very similar, country-by-country, using an alternative measure of skill abundance in which we set the ratio of $H_n/\left(H_n+L_n\right)$ across countries equal to the ratio of the average years of education in these countries, as reported in Barro and Lee (2010). We parameterize the perfectly competitive version of our model, presented in the Perfect Competition Appendix, and obtain almost identical results.

As discussed above, there is potentially more than one combination of trade costs and aggregate productivities that matches our target moments, since we have $N-1$ more parameters than moments. Here we consider three alternative parameterizations in which we restrict trade costs, as is standard in the literature. First, we eliminate $N-1$ parameters by restricting trade costs to be symmetric for ROW. Second, we eliminate $N-1$ parameters by restricting trade costs to be symmetric for the US. Finally, we restrict all trade costs to be symmetric. In all cases we obtain very similar results on the value of θ, the impact of trade on the skill premium and real wages, and the qualitative relationship between trade costs and observables.

In our final two sensitivity exercises we choose alternative assumptions that strengthen the H-O mechanism. In the first, we assume that $A_n\left(j\right)=A_n$—consistent with empirical evidence in Morrow (2010)—and do not match the extent of between sector trade that we target in moment 4 in our baseline parameterization. As shown in Figure 1, this yields too much between-sector specialization in the model relative to the data, strengthening the

H-O mechanism in most countries. In particular, the maximum (minimum) change in the skill premium rises (falls) from +19.65% (+2.12%) in our baseline to +23.23% (+0.81%) in this alternative specification. Nevertheless, consistent with our previous results, the H-O mechanism is still weak relative to the skill-biased technology mechanism; e.g., the skill premium rises even in skill-scarce countries.

In practice, firms within a sector may have heterogeneous skill intensities that are not systematically correlated with productivity, in which case the H-O mechanism is active within sectors. In our final sensitivity exercise we consider an extended version of the model in which $\alpha_j(\omega)$ depends both on the average sector j skill intensity, α_j which is parameterized using the ACS as in the baseline, as well as a random component ε, where $\varepsilon \sim \ln \mathcal{N}(0, \sigma_\alpha)$ is distributed log normal. Specifically, we assume that $\alpha_j(\omega) = \min\{\alpha_j \varepsilon, 1\}$ and continue to impose that $\alpha_j(\omega)$ is common across countries.

Increasing σ_α raises the dispersion of skill intensities across firms within sectors. Specifically, the standard deviation in $\log[h_i/(h_i + l_i)]$ across firms i within the median sector in country n relative to the standard deviation in skill intensity $\log[H_n(j)/(H_n(j) + L_n(j))]$ between sectors in country n is increasing in σ_α. This ratio equals to 0.21 in the US in our baseline in which $\sigma_\alpha = 0$ and it rises by a factor of 20 if $\sigma_\alpha = 0.2$. Given data availability, we could use this information to assign a value to σ_α. Note that if we impose $\varphi = 0$, then within a sector exporting firms are less skill intensive in a country with a high skill premium (a country with a low relative skill endowment H_n/L_n). For such a country, this results in a counterfactual negative elasticity of firm skill intensity to firm sales. Hence, this extension does not change the fact that matching moment 3 requires $\varphi > 0$.

As expected, increasing σ_α strengthens the H-O mechanism. For example, if we set σ_α as high as $\sigma_\alpha = 0.2$, the maximum increase in the skill premium rises from 19.65% to 28.62% and the minimum increase in the skill premium falls from 2.12% to -1.67%. Even in this case, the skill premium declines in only one country, China. Hence, the skill-biased technology mechanism remains significantly stronger than the H-O mechanism in most countries.

5 Alternative Approaches

In this section we discuss, through the lens of our model, three alternative approaches that have been used in the literature to study the impact of trade on the skill premium. These alternative approaches, rather than specifying a full GE model as we do, focus on: (*i*) the factor content of trade, (*ii*) the extent of between-sector factor reallocation, and (*iii*) the extent of sector-level relative price changes. We show that using these alternative approaches in our model leads in general to underestimating the impact of trade on the skill premium in both skill-abundant and skill-scarce countries.

5.1 The Factor Content of Trade

According to Krugman (2000), "...many economists studying the impact of trade on wages have been reluctant to commit themselves to a specific CGE model. Instead, they have tried to use a shortcut, by estimating the 'factor content' of trade." Burstein and Vogel (2011), show that an approach of this form is justifiable by decomposing the skill premium into two sufficient statistics in a general accounting framework,

$$\frac{s_n}{w_n} = \frac{L_n - FCT_n(L)}{H_n - FCT_n(H)} \times \frac{\Phi_n(H)}{\Phi_n(L)}.$$

The first sufficient statistic is the factor content of trade adjusted relative factor supply, where $FCT_n(L)$ is the amount of unskilled labor used to produce n's exports minus the counterfactual amount of unskilled labor that would be used in country n if country n produced domestically the value of the goods it imports. The second component is the ratio of factor payments for domestic absorption (FPD), where $\Phi_n(L)$ are the counterfactual payments to unskilled labor in country n if all domestic absorption were produced domestically. Precise definitions of the two sufficient statistics are provided in the Parameterization Appendix.

Under the assumptions that aggregate sector-level profit shares and factor intensities are independent of the destination to which goods are shipped, the factor content of trade simplifies to

$$FCT_n(L) = \sum_j (\text{Employment of } L_n \text{ in sector } j) \frac{NX_n(j)}{Y_n(j)}, \tag{19}$$

which can be measured using disaggregated sector-level data. Moreover, under the assumption that preferences and production functions are Cobb Douglas, $\Phi_n(H)/\Phi_n(L)$ is constant across equilibria.

A number of papers in the literature have measured the impact of international trade on the skill premium using equation (19); see e.g. Katz and Murphy (1992). However, a key assumption under which equation (19) is the appropriate measure of the FCT, that factor intensity is independent of the destination to which goods are shipped, is typically violated in the data. Instead, as discussed above, exporting firms are on average more skill intensive than domestic firms. We now show that, in our model with skill-biased technology, using the standard measure of the FCT displayed in equation (19) results in a large and systematic downward bias in the predicted impact of trade on the skill premium.

We show this graphically in the top panel of Figure 9. Using data generated by the model in the counterfactual in which we move from autarky to the baseline parameterization with full factor mobility, we plot the model's predicted change in the skill premium against the change in the skill premium implied by equation (19) for each country.

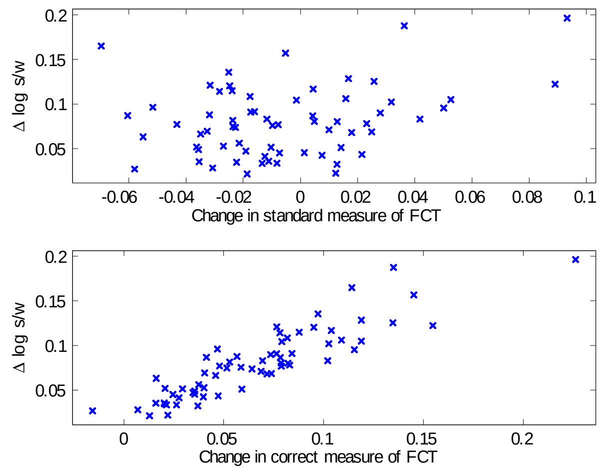

Figure 9: Changes in the factor content of trade and the skill premium for each country.

Whereas this standard approach predicts that the skill premium falls in 40 out of 65 countries, those that are skill scarce and hence are net exporters of unskill-intensive goods, the model predicts that it rises in all countries. Moreover, for those 25 countries in which the standard approach correctly predicts that the skill premium should rise, the rise in the skill premium implied by equation (19) accounts on average for only 30% of the actual rise in the skill premium.[33]

In the bottom panel of Figure 9 we plot the model's predicted change in the skill premium against the change in the skill premium using the correctly measured FCT. This version of the FCT does a significantly better job than the standard measure of the FCT. In particular, it predicts the right sign in the change of the skill premium for 64 out of 65 countries. Moreover, for those countries in which it predicts the right sign, it accounts on average for 81% of the actual rise in the skill premium. The remaining 19% is accounted for by changes in the second sufficient statistic, the FPD.

5.2 Factor reallocation

A number of empirical papers measure the extent of between-sector factor reallocation to assess the impact of international trade on inequality; see e.g. Berman et. al. (1994) in the

[33]The change in the skill premium implied by equation (19) is much more accurate when the skill-biased technology mechanism is inactive. If we fully re-parameterize the model imposing $\varphi = 0$, the correlation between the actual change in the skill premium and the change in the skill premium implied by equation (19) is equal to 0.97.

US and Attanasio et. al. (2004) in Colombia. Intuitively, if $\phi = 1/2$ as in the standard H-O model, then only between-sector factor reallocation affects the relative demand for skill and the skill premium. However, these and other studies—see e.g. the Goldberg and Pavcnik (2007) literature review—document relatively little between-sector labor reallocation. Moreover, other studies document substantially more within-sector than between-sector labor reallocation; see e.g. Haltiwanger et. al. (2004) for results in several Latin American countries. These findings have been interpreted through the lens of the H-O model as evidence that international trade is not responsible for much of the rise in inequality.

In our model, however, the rise in the skill premium is accompanied by significantly more within-sector than between-sector labor reallocation. Figure 10 illustrates this pattern using merchandise data generated by the model from our autarky-to-baseline counterfactual with full labor mobility for one Latin American country, Chile. In this counterfactual, the skill premium in Chile rises by 7.5%. Figure 10 reports net employment changes and within-sector reallocation by sector. The net employment change in a sector is defined, following Haltiwanger et. al. (2004), as the net employment change between two dates divided by the average employment in that sector across those two dates. Within-sector reallocation in a sector is defined as the weighted average across firms within a sector of the absolute firm-level employment change between two dates divided by the average employment in that firm across those two dates. We report separately within-sector reallocation for all firms and for continuing firms.

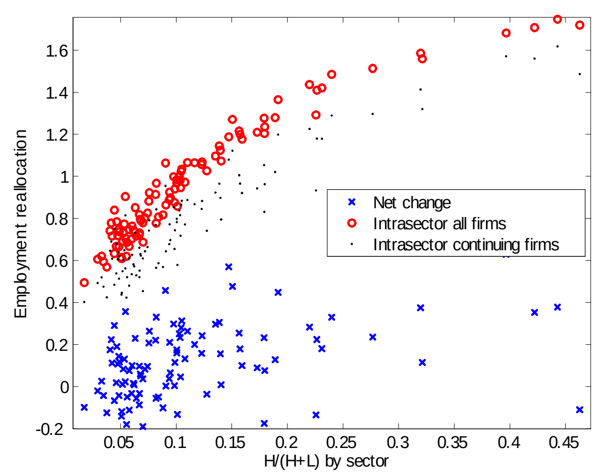

Figure 10: Net factor reallocation across firms within sectors and across sectors in Chile, moving from autarky to the baseline parameterization.

Three patterns emerge from Figure 10. First, sector-level net employment changes are not strongly related to factor intensity for Chile. While skill-intensive sectors expand on average, there is extensive heterogeneity in net employment changes across sectors with similar factor intensities. Second, within-sector reallocation—using both measures—is significantly larger than net employment changes for all sectors. Third, within-sector reallocation is larger for skill-intensive sectors. While there is some variation across countries in the extent to which net employment changes are related to factor intensities, the results that within-sector reallocation is significantly greater than between-sector reallocation and that within-sector reallocation is larger in skill-intensive sectors is quite robust across countries. The first two of these patterns stem from the fact that, with substantial productivity dispersion within sectors, $\theta = 0.25$, our model predicts relatively more within-sector reallocation than between-sector reallocation.

The third pattern stems from the interaction between skill-biased technology and skill-intensity variation across sectors. According to condition (18), within-sector dispersion in costs is larger in more skill-intensive sectors. This implies that there is a force in our model that generates more selection—both on the export margin and the exit margin—in skill-intensive sectors in all countries. Specifically, there is more exporting and, therefore, more firms that exit in sectors with greater unit cost dispersion. By condition (18), these are the skill-intensive sectors.[34] Because condition (18) generates more selection in skill-intensive sectors, it also causes more within-sector factor reallocation from exiting and domestic firms towards exporting firms.

We conclude that our model can generate a large impact of trade liberalization on the skill premium while being consistent with the empirical regularity that trade liberalization does not generate substantial between-sector reallocation.

5.3 Prices

Other empirical papers use changes in producer prices of skill-intensive relative to unskill-intensive sectors to measure the impact of international trade on inequality; see e.g. Lawrence and Slaughter (1993), Sachs and Shatz (1994), and Feenstra and Hanson (1999). The objective of this approach is to estimate the impact of trade on the relative producer price of skill-intensive sectors to infer the impact of trade on the skill premium. This approach builds on the assumption of perfect competition, so that goods prices reflect only changes in factor prices and productivities. Specifically, this approach infers the impact of changing goods prices (caused either by international trade or productivity) on factor prices using the zero profit condition, which equates each good's price with its unit cost of production, which

[34] Note that this result differs from that in Bernard et. al. (2007a), which predicts that selection is greater in a country's comparative advantage sector.

itself depends on unit factor requirements and factor prices. This approach implies that if international trade raises (lowers) the relative price of skill-intensive sectors, then it raises (lowers) the skill premium.

Using this approach in our model leads to a systematic underestimation of the impact of international trade on the skill premium. This bias results from the combination of variable markups and the interaction between skill-biased technology and skill-intensity variation across sectors.

In our model with Bertrand competition, changes in prices reflect not only changes in factor prices and factor requirements, but also changes in markups. Hence, if markups fall relatively more (less) in more skill-intensive sectors in response to a reduction in trade costs, then the sectoral-price approach will underestimate (overestimate) the rise in the skill premium caused by international trade. The reason is straightforward. In our model, a good's price equals its unit cost times its markup. If trade generates a larger reduction in markups in more skill-intensive sectors, then, all else equal, trade generates a larger reduction in prices in these sectors. If we take such goods-level price data and incorrectly assume that markups are fixed (as they are with perfect competition), then we will infer that costs fell relatively more in skill-intensive sectors and, therefore, we will underestimate the increase in the skill premium.

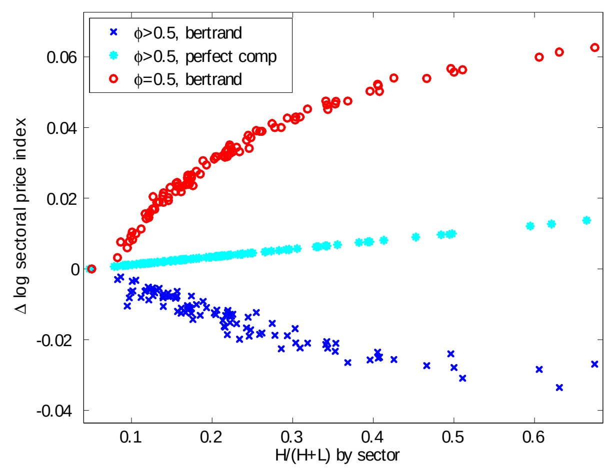

Figure 11: Changes in producer prices by sector in the US, moving from autarky to the baseline parameterization.

In our model, international trade does reduce markups relatively more in skill-intensive sectors. This follows from the interaction between skill-biased technology and skill-intensity variation across sectors. This interaction leads to greater unit cost dispersion in more skill-intensive sectors (see condition 18), so that reductions in trade costs lead to a larger rise in imports and a larger fall in markups in more skill-intensive sectors.[35]

[35] Relatedly, Edmond, Midrigan, and Xu (2011) study the extent to which standard approaches underes-

Figure 11 plots the average change in producer prices by sector, using data generated by our model for the US in the autarky to baseline parameterization counterfactual with full labor mobility.[36] We normalize the log change in the price of the least skill-intensive sector to zero. In our baseline parameterization, the 2% rise in the skill premium in the US is accompanied by a roughly 3.5% reduction in the price of the most skill-intensive sector relative to the least skill-intensive sector. Both variable markups and the interaction between skill-biased technology and skill-intensity variation across sectors are necessary to generate this pattern. To see this, Figure 11 also includes a plot of relative sectoral price changes under the assumption of skill-biased technology and perfect competition. In this case the rise in the skill premium necessarily results in a rise in the relative price of skill-intensive sectors. Figure 11 also includes a plot with Hicks-neutral technology, as in the standard H-O model, and Bertrand competition. Here, markups in the US fall relatively more in unskill-intensive sectors, where the rise in imports is greatest. This results in an even larger increase in the relative price of skill-intensive sectors as the skill premium rises.

We conclude that in our model with variable markups and skill-biased technology, trade liberalization can result in a simultaneous rise in the skill premium and fall in the relative price of skill-intensive goods. Hence, through the lens of our model, empirical approaches based on the premise that international trade moves the relative price of skill-intensive sectors and the skill premium in the same direction will underestimate the impact of trade on the skill premium.[37]

6 Conclusions

In this paper we have embedded into an otherwise standard quantitative trade model two of the central mechanisms proposed in the theoretical and empirical trade literature through which international trade shapes the skill premium: (*i*) trade induces factor reallocation towards skill (unskill) intensive sectors in skill-abundant (scarce) countries, and (*ii*) trade induces factor reallocation towards skill-intensive producers within sectors. Parameterized to 64 countries and the rest of the world, we find that much of the gains from trade accrue to skilled labor rather than unskilled labor because the skill premium rises in most countries in response to reductions in trade costs. For instance, we show that a skilled worker's real wage rises by 23% while an unskilled worker's real wage rises by only 4% in Costa Rica in response to a move from autarky to 2005-2007 trade shares with sectoral labor mobility.

timate the gains from trade in the presence of variable markups.

[36] For each sector we construct a weighted average of log domestic price changes by US producers selling both in autarky and in our baseline parameterization.

[37] Note that we have abstracted from changes in endowments and productivities, which are key to fully account for observed changes in the skill premium and sector prices.

Because our model accounts for the fact that more productive, larger, and exporting firms are more skill intensive than less productive, smaller, and domestic firms, it does not yield an analytic gravity equation at any level of aggregation. To deal with this complication, we use a new computational approach that quite accurately matches bilateral exports but does not require an analytic gravity equation at any level of aggregation. This approach can be applied in other applications that do not yield analytic gravity equations.

Whereas in this paper we capture two important forces in the debate on international trade and the skill premium, the H-O and skill-biased mechanisms, we abstract from other potentially important considerations discussed in the literature. We have abstracted from within-firm factor reallocation. In practice, reductions in trade costs cause multi-product firms to reallocate labor towards their export products and cause importing firms to offshore their least productive tasks. These forces, which can easily be incorporated into our model by redefining a firm as a set of productivity draws either across products or tasks, both magnify the strength of the skill-biased technology mechanism. We have not allowed for endogenous changes in the supply of skilled and unskilled labor, endogenous skill-biased technical innovation (see e.g. Acemoglu 2003), and trade in capital goods with capital-skill complementarity (see e.g. Burstein et. al. 2011 and Parro 2011). Finally, introducing non-homothetic preferences would lead to differences between changes in the nominal and the real skill premia; see e.g. Fajgelbaum et. al. (2011). Extending our model along these directions is a fruitful area for future research to fully assess the quantitative effects of international trade on the skill premium.

While in this paper we have focused on the impact of international trade on the skill premium, multinational production (MP) is another major form of globalization. For example, in 2006, sales of majority-owned, non-bank US foreign affiliates were more than twice as large as US exports. MP and FDI have implications, through the H-O and skill-biased mechanisms, for the skill premium. MP may strengthen the H-O effect, as high productivity firms are not constrained to produce domestically, and can choose instead to produce their output in countries that have a comparative advantage in their sector. MP may also strengthen the skill-biased technology mechanism, as it promotes the international diffusion of the best technologies. It would be interesting to extend the model in the present paper to allow for FDI and MP, using an approach as in Ramondo and Rodriguez-Clare (2010).

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A Parameterization

See Appendix Table 1 for a list of the 65 countries (including the rest of the world) and the country-specific data used in parameterizing the model.

Inferring gross output: We construct gross output in merchandise for country n using

$$Y_n^{merch} = GDP_n \times \frac{Y_n}{VA_n} \times \frac{Y_n^{merch}}{Y_n}$$

where we obtain GDP_n for all countries from the WDI and where VA_n is value added in country n. For the countries with OECD IO tables, we have Y_n/VA_n and Y_n^{merch}/Y_n. For the remaining countries we impute Y_n/VA_n by projecting Y_n/VA_n for those countries with OECD IO tables on $\log(GDP$ per capita), the service share of GDP, and the manufacturing share of GDP (both from the WDI). The R^2 of this regression is close to 0.90. We then use the predicted relationship between Y_n/VA_n and the above observables to predict Y_n/VA_n. We predict Y_n^{merch}/Y_n in a similar manner, using the relationship between Y_n^{merch}/Y_n and the manufacturing share (from the WDI), and not including Luxembourg in the regression because it is an outlier. Here, the R^2 is only about 30%.

The merchandise share of absorption: We construct γ_n as follows. From equation (15), we have $P_nQ_n = Y_n - NX_n$. Within merchandise, we similarly have absorption in merchandise,

$\gamma_n P_n Q_n$, given by $\gamma_n P_n Q_n = Y_n^{merch} - NX_n^{merch}$. With no trade in services, $NX_n = NX_n^{merch}$. Combining these equations we obtain

$$\gamma_n = \frac{Y_n^{merch} - NX_n}{Y_n - NX_n},$$

which is the equation we use to determine γ_n in each country n.

Sectoral skill intensities: We set α_j to match the share of those employed in sector j with a tertiary degree in the US (restricting the sample to only respondents who are employed and currently working), which we obtain from the American Community Survey (ACS) from IPUMS for the years 2005-2007. The five most skill-intensive merchandise sectors and their skill intensities are Pharmaceutical and medicine manufacturing (0.61), Aerospace product and parts manufacturing (0.56), Computer and peripheral equipment manufacturing (0.55), Communication, audio, and video equipment manufacturing (0.47), and Forestry except logging (0.46). The five least skill-intensive merchandise sectors are Logging (0.04), Animal slaughtering and processing (0.07), Fiber, yarn, and thread mills (0.08), Carpets and rug mills (0.09), and Machine shops, turned product, screw, nut, and bolt manufacturing (0.09).

Given our production function, the share of skilled workers in sector j in our model does not exactly equal α_j. However, the share of workers in sector j with a tertiary degree in the US in the model is reasonably close to that in the data. The maximum and mean absolute differences between these two ratios in merchandise (service) sectors, in percentage points, are 10% and 4.6% (7.3% and 1.1%), respectively. Moreover, the share of workers in the US merchandise and service sectors with a completed tertiary degree in the model are 24% and 33%, whereas in the data they are 22% and 30%, respectively. The model slightly over predicts the share with a tertiary degree in the US because the share of employed US workers with a tertiary degree in ACS, 29%, is lower than the share in Barro and Lee (2010), 31%. We use Barro and Lee (2010) to measure the skill abundance of the US because it provides a comparable measure for the other countries. Given this discrepancy, it is impossible to choose αs to exactly match the share of workers with a tertiary degree in each sector in the US. In order to match both aggregate and sector-specific measures of skill intensity observed in the data, we would have to allow for exogenous differences in sector sizes, introducing an additional set of parameters. We choose to abstract from differences in sector size since our simple procedure already produce sector-specific skill intensities that are quite close to those in the data.

Accounting: Recall the parameters γ_n and nx_n are

$$\gamma_n = \frac{Y_n^{merch} - nx_n Y_n}{Y_n - nx_n Y_n} \tag{20}$$

and

$$nx_n = \left[\sum\nolimits_i X_{ni} - X_{in}\right] \Big/ Y_n.$$

Note that equation (20) implies

$$Y_n^{merch} = \kappa_n Y_n, \tag{21}$$

where $\kappa_n = \gamma_n + nx_n - \gamma_n nx_n$. Hence, given nx_n and γ_n, Y_n^{merch} uniquely determines Y_n.

The moments we take from the data are $x_{in} = X_{in}/\left(Y_i^{merch} + Y_n^{merch}\right)$ and $Y_i / \sum_n Y_n$. We now show that matching these moments is equivalent to matching the more standard moments $x'_{in} = X_{in}/Y_n^{merch}$. Clearly, x_{in} and $Y_i / \sum_n Y_n$ imply x'_{in}. Now, we show that x'_{in} implies $Y_i / \sum_n Y_n$

and, hence, x_{in}. The x'_{in}s must satisfy the following restriction

$$\sum_i x'_{in} = \frac{1}{Y_n \kappa_n} \sum_i X_{in} = \frac{1}{Y_n \kappa_n} \left(Y_n - NX_n\right) = \frac{1}{\kappa_n} \left(1 - nx_n\right), \tag{22}$$

where the first equality follows from equation (21), the second equality follows from the definition of NX_n, and the final equality follows from the definition of nx_n. Note that the x'_{in}s also satisfy the following restriction

$$Y_n = \sum_i X_{ni} = \sum_i x'_{ni} Y_i^{merch}, \tag{23}$$

which implies

$$\frac{Y_n}{Y_N} = \sum_i \frac{Y_i}{Y_N} \kappa_i x'_{ni}.$$

While this is a system of N equations in $(N-1)$ unknowns, Y_n/Y_N, only $(N-1)$ equations are independent because of restriction (22) and world trade balance, $\sum_n nx_n Y_n/Y_N = 0$. We can use these $N-1$ equations to solve for the $N-1$ relative outputs, Y_n/Y_N. Since x'_{in} implies Y_n/Y_N, it also implies $Y_i / \sum_n Y_n$. Thus, x'_{in} implies x_{in} and $Y_i / \sum_n Y_n$.

Finally, from restriction (22), of the $N \times N$ moments x'_{in}, only $N(N-1)$ are independent. Since x'_{in} is equivalent to x_{in} and $Y_i / \sum_n Y_n$, there are also only $N(N-1)$ independent targets in x_{in} and $Y_i / \sum_n Y_n$.

Solution algorithm—Inner loop: The inner loop is as follows. Given an initial guess of w_n, s_n, π_n in iteration number k_I, we first construct aggregate absorption in country n, $P_n Q_n$, as

$$P_n Q_n = \left(w_n L_n^d + s_n H_n^d\right)\left(1 + \pi_n\right)\left(1 - nx_n^d\right),$$

from equation (15) and $Y_n = s_n H_n + w_n L_n + \Pi_n$. Here d denotes a variable observed directly rather than constructed in the model.[38]

For a fixed set of firm productivity draws z, we then solve for all prices and the indicator functions, $p_n(\omega, j)$, $\mathbb{I}_{in}(\omega, j)$, $P_n(j)$, P_n, by finding the lowest-cost supplier in each country/variety and using the price equations (5), (6), and (7). Given prices, utility, and the demand equations (1) and (2), we solve for quantities, Q_n, $Q_n(j)$, and $q_n(\omega, j)$. Finally, we solve for output, $y_n(\omega, j)$, and labor demands, $l_n(\omega, j)$, $h_n(\omega, j)$, using equations (11) and (14).

We then construct the implied factor demands in the model, L_n^m and H_n^m, using equations (12) and (13), the aggregate output in the model Y_n^m using equation (8), and the aggregate profits in the model using $\Pi_n^m = Y_n^m - w_n L_n^m - s_n H_n^m$. Here, m denotes a variable constructed in the model that we will compare with its value observed in the data, indicated by d, in order to update our guesses. We similarly construct aggregate exports, $\sum_{i \neq n} X_{ni}^m$, and net exports, NX_n^m, in the model using equation (9) as well the definition of net exports.

Using L_n^m and H_n^m we construct the excess relative demand for skilled labor implied by the model,

$$f_n^1 = \left(\frac{H_n^m}{L_n^m} - \frac{H_n^d}{L_n^d}\right) \Big/ \left(\frac{H_n^d}{L_n^d}\right).$$

[38] For ROW (country N) we choose nx_N^d so that there is balanced trade in the aggregate world economy rather than directly from data. Note that once the algorithm is terminated, constructed net exports in the model equal net exports in the data for ROW.

Similarly, we construct excess net exports,

$$f_n^2 = \frac{NX_n^m - \left(w_n L_n^d + s_n H_n^d\right)\left(1+\pi_n\right) nx_n^d}{\sum_{i\neq n} X_{ni}^m}.$$

We then update our guess of equilibrium wages and profits (used in iteration k_I+1) as follows,

$$\begin{aligned}
\left(\frac{s_n}{w_n}\right)^{k_I+1} &= \left(\frac{s_n}{w_n}\right)^{k_I} \times \left(1+\Delta^{s/w} f_n^1\right) \\
w_n^{k_I+1} &= w_n^{k_I} \times \left(1+\Delta^w f_n^2\right) \\
s_n^{k_I+1} &= w_n^{k_I+1} \times \left(\frac{s_n}{w_n}\right)^{k_I+1} \\
\left(\pi_n\right)^{k_I+1} &= \Pi_n^m \Big/ \left(s_n^{k_I} H_n^d + w_n^{k_I} L_n^d\right)
\end{aligned}$$

where factor prices are re-scaled such that $\sum_i \left(s_i^{k_I+1} H_i^d + w_i^{k_I+1} L_i^d\right) = \overline{W}$; that is, we normalize $\sum_n \left(s_n H_n + w_n L_n\right)$. We terminate the loop when $\left|f_n^1\right|$, $\left|f_n^2\right|$, and $\left|\left(\pi_n\right)^{k_I+1} - \left(\pi_n\right)^{k_I}\right|$ are sufficiently small.

Solution algorithm—Middle loop: The middle loop is as follows. Given an initial guess of τ_{ni}, T_n, and t_n in iteration number k_M and using equilibrium variables generated from the inner loop, we construct

$$\begin{aligned}
f_{ni}^\tau &= x_{ni}^m / x_{ni}^d - 1 \\
f_n^T &= \left(\frac{Y_n^m}{\sum_i Y_i^m}\right) \Big/ \left(\frac{Y_n^d}{\sum_i Y_i^d}\right) - 1 \\
f_n^\beta &= \beta_n^m - \overline{\beta}^m - \left(\beta_n^d - \overline{\beta}^d\right).
\end{aligned}$$

We choose new guesses for τ_{ni}, T_n, and t_n (used in iteration k_M+1) according to

$$\begin{aligned}
\tau_{ni}^{k_M+1} &= 1 + \left(\tau_{ni}^{k_M} - 1\right) \times \left[1+\Delta^\tau f_{ni}^\tau\right] \\
T_n^{k_M+1} &= T_n^{k_M}\left[1+\Delta^T f_n^T\right] \\
t_n^{k_M+1} &= t_n^{k_M} + \Delta^\beta f_n^\beta.
\end{aligned}$$

Note that while we are solving for one T_n per country, only relative T_ns matter for equilibrium allocations and relative prices.

We terminate the loop when $\left|f_n^T\right|$, $\left|f_n^\beta\right|$, and the difference between aggregate country n exports relative to merchandise output in the model and the data—i.e., $\left|\frac{\sum_{i\neq n} X_{ni}^m}{\left(Y_i^{merch}\right)^m} - \frac{\sum_{i\neq n} X_{ni}^d}{\left(Y_i^{merch}\right)^d}\right|$—are small. In practice, this implies that the difference between *bilateral* exports relative to merchandise output in the model and the data—i.e., $|f_{ni}^\tau|$s—are also small, as we show in Figure 2.

The factor content of trade exercise: Using a general accounting framework, Burstein and

Vogel (2011) show that the skill premium can be decomposed into two sufficient statistics,

$$\frac{s_n}{w_n} = \frac{L_n - FCT_n(L)}{H_n - FCT_n(H)} \times \frac{\Phi_n(H)}{\Phi_n(L)},$$

where the first sufficient statistic is the factor content of trade adjusted relative factor supply and the second sufficient statistic is the ratio of factor payments for domestic absorption (FPD). Under the assumptions of our model we have

$$\begin{aligned} FCT_n(L) &= \sum\nolimits_j \sum\nolimits_i \left[L_{ni}(j) - L_{nn}(j) \frac{\Lambda_{in}(j)}{\Lambda_{nn}(j)} \right], \\ FCT_n(H) &= \sum\nolimits_j \sum\nolimits_n \left[H_{ni}(j) - H_{nn}(j) \frac{\Lambda_{in}(j)}{\Lambda_{nn}(j)} \right], \end{aligned}$$

and

$$\Phi_n(L) = \sum\nolimits_j \frac{w_n L_{nn}(j)}{\Lambda_{nn}(j)} \quad \text{and} \quad \Phi_n(H) = \sum\nolimits_j \frac{s_n H_{nn}(j)}{\Lambda_{nn}(j)},$$

where $\Lambda_{in}(j)$ is the share of country n's sector j expenditure allocated to varieties produced in country i, and where $L_{ni}(j) = \int_0^1 l_{ni}(\omega, j)\, d\omega$ and $H_{ni}(j) = \int_0^1 h_{ni}(\omega, j)\, d\omega$ are the amount of country n unskilled and skilled labor used in supplying sector j varieties in country i. Constructing $L_{in}(j)$ and $H_{in}(j)$ requires detailed information on firm employment by export destination that is typically unavailable in practice. However, under the assumptions that aggregate sector-level profit shares and factor intensities are independent of the destination to which goods are shipped, the FCT equations simplify to equation (19).

To generate the log change in the skill premium using the correctly measured FCT, we construct $FCT_n(L)$ and $FCT_n(H)$ using data generated by the model in the baseline parameterization and in autarky. The log change in the skill premium using the correctly measured FCT is then simply the log ratio of $\frac{L_n - FCT_n(L)}{H_n - FCT_n(H)}$ in the baseline relative to $\frac{L_n - FCT_n(L)}{H_n - FCT_n(H)}$ in autarky. To generate the change in the skill premium using the incorrectly measured FCT, we conduct the same exercise using the version of the factor content of trade shown in equation (19) rather than the correct version.

B Sensitivity

In all sensitivity analyses, we consider the counterfactual exercise in which we move countries from autarky to alternative versions of the 2005-2007 parameterization with full factor mobility, making the changes indicated below.

Perfect competition: In this table we consider the perfectly competitive version of our model, holding fixed the values of $\{\rho, \varphi, \theta\}$ and re-running the middle and inner loops:

	Baseline	Perfect competition
mean	+8.00	+7.89
max	+19.65	+19.82
min	+2.12	+1.88

The market structure in the present paper is not central for our results, as we obtain extremely similar results country-by-country under perfect competition. Note, however, that imperfect competition is important for allowing us to match firm- and plant-level data in the model. Specifically, we are imposing the same φ in the perfectly competitive model as in our baseline model.

Skill bias of technology: In this table we consider alternative values for φ (by varying ϕ). We hold fixed $\{\rho,\theta\}$ and re-run the middle and inner loops:

	Baseline	Hicks-Neutral				
	$\varphi = 0.4$	$\varphi = 0$	$\varphi = 0.08$	$\varphi = 0.24$	$\varphi = 0.64$	$\varphi = 0.72$
mean	+8.00	−0.2	+1.14	+4.28	+13.83	+15.64
max	+19.65	+2.67	+4.05	+11.41	+33.19	+37.99
min	+2.12	−2.56	−1.01	+0.6	+3.04	+3.28

As expected, the skill-biased technology mechanism becomes stronger as we increase φ.

Heterogeneity: In this table we consider alternative values for θ. We hold fixed $\{\rho,\varphi\}$ and re-run the middle and inner loops:

	Baseline			
	$\theta = 0.25$	$\theta = 0.125$	$\theta = 0.17$	$\theta = 0.3$
mean	+8.00	+3.60	+5.15	+9.74
max	+19.65	+10.34	+13.56	+23.20
min	+2.12	0	+0.93	+2.45

The H-O mechanism becomes weaker and the skill-biased technology mechanism becomes stronger as we increase θ. The overall effect of increasing θ is to increase the impact of trade on the skill premium, on average.

Elasticity of substitution across goods: Changing σ affects the strength of both the H-O and the skill-biased technology mechanisms. With $\varphi > 0$, reductions in trade costs reduce the relative price of skill-intensive sectors because of the interaction between skill-biased technology and skill-intensity variation across sectors. In response to this change in relative prices, consumers are more willing to substitute towards skill-intensive sectors the higher is σ. Hence, a higher value of σ strengthens the skill-biased technology mechanism. On the other hand, with $\varphi = 0$, reductions in trade costs increase the relative price of a country's comparative advantage sector. In response to this change in relative prices, consumers are more willing to substitute away from the comparative advantage sector the higher is σ. Hence, a higher value of σ weakens the H-O mechanism.

In this table we consider alternative values for σ. We fully re-parameterize the model in all but the last column. In the second column we choose $\sigma = 2.2$ to match the median 3-digit SITC elasticity of substitution between 1990 and 2001 estimated by Broda and Weinstein (2006). In the third column we set $\sigma = 1$ so that there are constant sectoral expenditure shares. The skill premium change is about half as large in the third column as in our baseline for two reasons. First, with $\sigma = 1$ the reduction in the strength of the skill-biased technology mechanism more than outweighs the increase in strength of the H-O mechanism. Second, with $\sigma = 1$, matching our first target ($\widehat{\rho} = 1.6$) requires setting the elasticity of substitution between skilled and unskilled workers at the firm level to $\rho = 1.6$ rather than $\rho = 1.4$ in our baseline. To isolate the direct effect of reducing σ

to 1, in the fourth column we set $\sigma = 1$ but, rather than matching our first target, we fix ρ at its baseline level of $\rho = 1.4$ (which implies $\widehat{\rho} = 1.38$).

	Baseline			$\rho = 1.4$
	$\sigma = 2.7$	$\sigma = 2.2$	$\sigma = 1$	$\sigma = 1$
mean	+8.00	+6.94	+3.96	+6.24
max	+19.65	+17.9	+12.10	+18.21
min	+2.12	+1.53	−0.3	+0.3

Alternative trade cost and aggregate productivity parameterizations: Here we consider three alternative parameterizations in which we restrict trade costs, as is standard in the literature. First, we eliminate $N-1$ parameters by restricting trade costs to be symmetric for ROW (country N). In this case, we still target x_{in} for all $i, n \neq N$ as in the baseline parameterization; to gain efficiency in our algorithm, we now target $x_{iN} + x_{Ni}$ rather than targeting x_{iN} and x_{Ni} independently. In this case, we have the same number of parameters and moments. Second, we eliminate $N-1$ parameters by restricting trade costs to be symmetric for the US following the same approach. Finally, we restrict all trade trade costs to be symmetric. In all cases we obtain very similar results on the value of θ, the impact of trade on the skill premium (as we show in the table below) and real wages, and the qualitative relationship between trade costs and observables.

	Baseline	symmetric trade costs in ROW	symmetric trade costs in US	symmetric trade costs in all n
mean	+8.00	+8.00	+8.00	+8.08
max	+19.65	+19.63	+19.63	+19.47
min	+2.12	+2.12	+2.12	+2.12

Sector-level productivity differences and different measures of factor endowments: In these two cases, we hold $\{\rho, \varphi, \theta\}$ fixed and re-run the middle and inner loops. In the first table, we do not target moment 4 (imposing $t_n = 0$ in all countries):

	Baseline	Setting $t_n = 0$
mean	+8.00	+9.27
max	+19.65	+23.23
min	+2.12	+0.81

In the second table, we choose an alternative measure for countries' skill abundance—average years of education from Barro and Lee (2010)[39]—first targeting moment 4 and then not targeting moment

[39] In particular, we set $H_{US}/(H_{US} + L_{US})$ at our baseline level (based on the fraction of the workforce with complete tertiary), and set $H_n/(H_n + L_n) = H_{US}/(H_{US} + L_{US}) \times$ average years of education in country n / average years of education US.

4:

	Baseline	$\frac{H_n}{L_n}$ avg yrs of educ.	$\frac{H_n}{L_n}$ avg yrs of educ. and setting $t_n = 0$
mean	+8.00	+7.90	+9.80
max	+19.65	+19.40	+22.63
min	+2.12	+2.01	+1.84

There are two points made by these tables. First, the H-O mechanism becomes stronger if we do not target our fourth moment, and instead impose $t_n = 0$ for all countries. This is evident from the increased dispersion in the change in the skill premium. Note that Figure 1 already hinted that the H-O would be stronger with $t_n = 0$ since that figure reveals that with setting $t_n = 0$, the model generates correlation between $\beta_n - \overline{\beta}$ and $H_n / (H_n + L_n)$ that is stronger than in the data. Second, the specific measure of skill abundance does not seem to affect our results, especially if we target our fourth moment. If we target our fourth moment, the results are almost identical, country-by-country, whether we choose $H_n / (H_n + L_n)$ to match the share of workers with a tertiary degree or the average years of education.

Heterogeneity in α within sectors: We now allow for heterogeneity in skill intensity within sectors that is uncorrelated with firm productivity. We assume that

$$\alpha_j(\omega) = \min\left\{\overline{\alpha}_j \exp(\varepsilon), 1\right\},$$

where $\varepsilon \sim \ln \mathcal{N}(0, \sigma_\alpha)$. This strengthens the H-O mechanism, because H-O forces now operate within sectors. If we impose $\varphi = 0$, within a sector exporters are relatively less skill intensive than domestic firms in high s/w countries. This results in a counterfactual negative elasticity of firm skill intensity to firm sales in such countries. Clearly, in order to match target 3 we need $\varphi > 0$. In the following table we consider two alternative values of σ_α—0.05, 0.1, and 0.2—in addition to our baseline value of $\sigma_\alpha = 0$. For each value of σ_α we re-run the outer, middle and inner loops. Note that higher values of σ_α require lower values of ρ, because there is more within-sector reallocation in response to a change in H in the US. In this table we also report, for the US, the standard deviation of skill intensities across firms within the median sector, relative to the standard deviation of the average sectoral skill intensity across sectors. As discussed above, given data availability one could use this information to assign a value to σ_α.

	Baseline $\sigma_\alpha = 0$	$\sigma_\alpha = 0.05$	$\sigma_\alpha = 0.1$	$\sigma_\alpha = 0.2$
Standard deviation log h/l (median sector within) / btw	0.21	0.66	2	4.2
mean	+8.00	+8.32	+9.64	+10.84
max	+19.65	+20.26	+24.07	+28.62
min	+2.12	+2.09	+1.73	−1.67

As expected, increasing σ_α strengthens the H-O mechanism. Even with σ_α as high as $\sigma_\alpha = 0.2$, the skill premium declines in only one country, China. Hence, the skill-biased technology mechanism remains significantly stronger than the H-O mechanism in most countries.

Appendix Table 1: Country-level data used in model parameterization

Country name		Fraction US$ output in world output	Fraction tertiary complete, H/(H+L)	Merchandise share of absorption, γ	Trade / merchandise output		Net exports relative to total output	Net exports and skill intensity, β-βbar
					Exports	Imports		
Argentina	ARG	0.0039	0.037	0.347	0.339	0.232	0.040	-1.533
Australia	AUS	0.0160	0.206	0.256	0.305	0.318	-0.003	-0.586
Austria	AUT	0.0067	0.107	0.320	0.590	0.646	-0.017	-0.339
Belarus	BLR	0.0009	0.089	0.570	0.328	0.437	-0.059	-1.311
Brazil	BRA	0.0227	0.058	0.412	0.150	0.092	0.025	-1.850
Bulgaria	BGR	0.0007	0.123	0.459	0.511	0.845	-0.130	-0.396
Canada	CAN	0.0245	0.319	0.342	0.438	0.388	0.018	-0.487
Chile	CHL	0.0030	0.105	0.328	0.484	0.296	0.070	-1.228
China	CHN	0.0820	0.032	0.587	0.234	0.123	0.069	-1.317
Colombia	COL	0.0035	0.088	0.416	0.180	0.171	0.004	-2.033
Costa Rica	CRI	0.0005	0.134	0.374	0.690	0.494	0.084	0.859
Croatia	HRV	0.0011	0.042	0.426	0.234	0.572	-0.121	-0.181
Cyprus	CYP	0.0004	0.168	0.322	0.384	0.792	-0.103	0.928
Czech Republic	CZE	0.0040	0.067	0.452	0.480	0.523	-0.019	-0.777
Denmark	DNK	0.0057	0.114	0.262	0.558	0.561	-0.001	0.182
Dominican Republic	DOM	0.0008	0.040	0.469	0.172	0.258	-0.039	0.934
Ecuador	ECU	0.0008	0.101	0.371	0.458	0.365	0.037	-0.876
El Salvador	SLV	0.0004	0.077	0.511	0.187	0.401	-0.099	-0.217
Estonia	EST	0.0004	0.179	0.405	0.621	0.910	-0.100	-0.929
Finland	FIN	0.0048	0.150	0.365	0.437	0.377	0.023	-0.009
France	FRA	0.0463	0.100	0.289	0.365	0.394	-0.008	0.274
Germany	DEU	0.0598	0.137	0.347	0.482	0.411	0.026	-0.053
Greece	GRC	0.0047	0.214	0.300	0.180	0.565	-0.091	-0.339
Guatemala	GTM	0.0006	0.028	0.504	0.211	0.345	-0.063	-0.899
Honduras	HND	0.0002	0.032	0.481	0.474	0.433	0.020	-0.729
Hungary	HUN	0.0029	0.112	0.440	0.573	0.625	-0.022	0.222
Iceland	ISL	0.0003	0.144	0.333	0.346	0.578	-0.067	0.160
India	IND	0.0201	0.034	0.515	0.126	0.148	-0.011	-1.717
Indonesia	IDN	0.0071	0.016	0.487	0.317	0.165	0.080	-0.841
Ireland	IRL	0.0052	0.185	0.241	0.811	0.405	0.141	1.245
Israel	ISR	0.0030	0.274	0.274	0.532	0.485	0.013	1.364
Italy	ITA	0.0414	0.067	0.336	0.285	0.289	-0.001	-0.748
Jamaica	JAM	0.0002	0.087	0.418	0.281	0.705	-0.142	0.142
Japan	JPN	0.0826	0.215	0.343	0.227	0.187	0.014	0.723
Kazakhstan	KAZ	0.0016	0.108	0.387	0.457	0.364	0.038	-0.012
Korea, Rep.	KOR	0.0229	0.163	0.486	0.290	0.262	0.014	0.451
Latvia	LVA	0.0004	0.103	0.366	0.584	0.914	-0.100	-0.968
Lithuania	LTU	0.0007	0.167	0.458	0.429	0.740	-0.122	-0.407
Malaysia	MYS	0.0038	0.041	0.435	0.934	0.593	0.184	-0.036
Mexico	MEX	0.0163	0.125	0.408	0.370	0.370	0.000	0.645
Netherlands	NLD	0.0146	0.168	0.290	0.834	0.830	0.001	0.516
New Zealand	NZL	0.0027	0.224	0.329	0.271	0.317	-0.015	-1.005
Norway	NOR	0.0062	0.144	0.311	0.506	0.285	0.081	0.572
Paraguay	PRY	0.0002	0.029	0.487	0.278	0.534	-0.110	-0.946
Peru	PER	0.0019	0.167	0.411	0.267	0.187	0.035	-1.871
Philippines	PHL	0.0028	0.215	0.485	0.473	0.344	0.067	0.195
Poland	POL	0.0080	0.081	0.404	0.321	0.414	-0.035	-1.255
Portugal	PRT	0.0044	0.041	0.324	0.321	0.495	-0.050	-0.714
Romania	ROM	0.0028	0.057	0.465	0.267	0.446	-0.076	-0.343
Russian Federation	RUS	0.0196	0.218	0.390	0.345	0.164	0.079	0.197
Serbia	SRB	0.0006	0.082	0.524	0.169	0.462	-0.135	-0.851
Slovak Republic	SVK	0.0018	0.066	0.424	0.521	0.524	-0.001	-0.435
Slovenia	SVN	0.0009	0.093	0.414	0.535	0.643	-0.042	-0.572
Spain	ESP	0.0273	0.157	0.331	0.250	0.392	-0.043	-0.645
Sri Lanka	LKA	0.0006	0.097	0.491	0.253	0.337	-0.039	-0.278
Sweden	SWE	0.0087	0.180	0.320	0.503	0.445	0.019	0.477
Switzerland	CHE	0.0079	0.122	0.284	0.677	0.582	0.029	1.046
Thailand	THA	0.0049	0.062	0.554	0.485	0.419	0.038	-0.693
Turkey	TUR	0.0117	0.057	0.475	0.157	0.256	-0.045	-2.309
Ukraine	UKR	0.0025	0.249	0.484	0.351	0.358	-0.004	-0.349
United Kingdom	GBR	0.0503	0.119	0.239	0.353	0.495	-0.031	1.007
United States	USA	0.2451	0.310	0.268	0.166	0.299	-0.033	0.535
Uruguay	URY	0.0004	0.070	0.396	0.280	0.273	0.003	-1.560
Vietnam	VNM	0.0014	0.020	0.616	0.496	0.500	-0.003	-1.150
Rest of world	ROW	0.0702	0.081	0.400	0.442	0.479	-0.015	-0.372

Appendix Table 2: Counterfactual
Log change in real wage and skill premium

		Autarky to 2005-2007			10% in trade costs			
					Full factor mobility			Limited factor mobility
Country name		Real wage skilled	Real wage unskilled	Skill premium	Real wage skilled	Real wage unskilled	Skill premium	Skill premium merchandise
Argentina	ARG	0.0715	0.019	0.053	0.025	0.014	0.011	0.030
Australia	AUS	0.0502	0.017	0.033	0.019	0.010	0.009	0.041
Austria	AUT	0.1273	0.052	0.076	0.033	0.023	0.010	0.033
Belarus	BLR	0.1424	0.056	0.087	0.047	0.025	0.022	0.045
Brazil	BRA	0.0294	0.008	0.021	0.011	0.006	0.004	0.013
Bulgaria	BGR	0.2146	0.079	0.135	0.056	0.030	0.026	0.066
Canada	CAN	0.0746	0.033	0.041	0.027	0.018	0.009	0.029
Chile	CHL	0.0973	0.024	0.074	0.031	0.017	0.013	0.036
China	CHN	0.0525	0.018	0.035	0.017	0.014	0.004	0.008
Colombia	COL	0.0509	0.016	0.035	0.019	0.008	0.011	0.031
Costa Rica	CRI	0.2365	0.040	0.196	0.051	0.029	0.022	0.046
Croatia	HRV	0.1147	0.045	0.069	0.036	0.013	0.023	0.065
Cyprus	CYP	0.1410	0.039	0.102	0.039	0.012	0.028	0.093
Czech Republic	CZE	0.1455	0.058	0.088	0.042	0.027	0.015	0.035
Denmark	DNK	0.1048	0.034	0.071	0.028	0.017	0.011	0.041
Dominican Republic	DOM	0.1006	0.020	0.080	0.034	0.008	0.026	0.058
Ecuador	ECU	0.1213	0.030	0.091	0.036	0.018	0.017	0.045
El Salvador	SLV	0.1198	0.038	0.081	0.038	0.012	0.026	0.061
Estonia	EST	0.2063	0.085	0.121	0.049	0.032	0.017	0.048
Finland	FIN	0.1091	0.029	0.080	0.032	0.016	0.016	0.042
France	FRA	0.0672	0.025	0.042	0.022	0.013	0.009	0.034
Germany	DEU	0.0834	0.038	0.045	0.027	0.020	0.007	0.023
Greece	GRC	0.0745	0.029	0.045	0.017	0.007	0.011	0.054
Guatemala	GTM	0.1125	0.036	0.077	0.038	0.013	0.025	0.053
Honduras	HND	0.2043	0.047	0.157	0.062	0.029	0.034	0.062
Hungary	HUN	0.1919	0.064	0.128	0.047	0.030	0.017	0.039
Iceland	ISL	0.1196	0.033	0.087	0.035	0.011	0.024	0.079
India	IND	0.0455	0.018	0.028	0.017	0.009	0.008	0.019
Indonesia	IDN	0.0943	0.018	0.077	0.029	0.015	0.014	0.028
Ireland	IRL	0.1513	0.029	0.122	0.030	0.023	0.007	0.019
Israel	ISR	0.1155	0.020	0.095	0.032	0.013	0.019	0.061
Italy	ITA	0.0559	0.022	0.033	0.019	0.012	0.007	0.025
Jamaica	JAM	0.1539	0.050	0.104	0.052	0.013	0.039	0.104
Japan	JPN	0.0438	0.011	0.032	0.016	0.008	0.008	0.027
Kazakhstan	KAZ	0.1342	0.028	0.106	0.039	0.019	0.020	0.046
Korea, Rep.	KOR	0.0922	0.024	0.068	0.033	0.016	0.016	0.036
Latvia	LVA	0.1870	0.073	0.114	0.044	0.027	0.017	0.055
Lithuania	LTU	0.1740	0.066	0.108	0.047	0.023	0.024	0.060
Malaysia	MYS	0.3433	0.156	0.188	0.058	0.063	-0.005	-0.005
Mexico	MEX	0.0993	0.031	0.068	0.034	0.018	0.016	0.041
Netherlands	NLD	0.1735	0.084	0.090	0.035	0.034	0.001	0.005
New Zealand	NZL	0.0673	0.020	0.047	0.023	0.010	0.014	0.050
Norway	NOR	0.0992	0.016	0.083	0.027	0.014	0.013	0.036
Paraguay	PRY	0.1486	0.052	0.096	0.049	0.022	0.027	0.064
Peru	PER	0.0643	0.015	0.049	0.026	0.011	0.015	0.040
Philippines	PHL	0.1569	0.032	0.125	0.047	0.024	0.023	0.045
Poland	POL	0.0903	0.039	0.052	0.028	0.017	0.012	0.034
Portugal	PRT	0.0893	0.033	0.056	0.029	0.014	0.015	0.053
Romania	ROM	0.1161	0.041	0.075	0.038	0.016	0.023	0.055
Russian Federation	RUS	0.0617	0.011	0.051	0.021	0.011	0.009	0.024
Serbia	SRB	0.1114	0.048	0.063	0.036	0.013	0.023	0.057
Slovak Republic	SVK	0.1690	0.052	0.117	0.043	0.026	0.017	0.039
Slovenia	SVN	0.1761	0.061	0.115	0.048	0.028	0.021	0.050
Spain	ESP	0.0628	0.027	0.036	0.019	0.011	0.008	0.032
Sri Lanka	LKA	0.1210	0.030	0.091	0.041	0.012	0.029	0.064
Sweden	SWE	0.1082	0.030	0.078	0.030	0.017	0.014	0.040
Switzerland	CHE	0.1455	0.040	0.105	0.034	0.023	0.011	0.032
Thailand	THA	0.1792	0.059	0.120	0.054	0.033	0.022	0.038
Turkey	TUR	0.0563	0.030	0.027	0.020	0.011	0.009	0.024
Ukraine	UKR	0.1178	0.035	0.083	0.038	0.019	0.019	0.043
United Kingdom	GBR	0.0657	0.022	0.043	0.019	0.010	0.010	0.045
United States	USA	0.0370	0.015	0.022	0.011	0.006	0.005	0.024
Uruguay	URY	0.0889	0.023	0.066	0.033	0.013	0.020	0.053
Vietnam	VNM	0.2429	0.078	0.165	0.066	0.039	0.027	0.043
Rest of world	ROW	0.0993	0.048	0.051	0.033	0.024	0.009	0.023
Mean		0.1185	0.0384	0.0800	0.0342	0.0183	0.0159	0.0422