Trade, Technology and Input Linkages: A Theory with Evidence from Colombia*

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Abstract

We develop a model of international trade with heterogeneous firms and endogenous technology choices. Firms interaction in the domestic input market amplifies the effects of international trade on technology choices. That is, if high- and low-technology firms value inputs equally, then a trade liberalization leads domestically-oriented firms to downgrade their technology. If, on the other hand, technologically advanced goods can only be made with technologically advanced inputs, then trade has an ambiguous effect on non-exporters technology choices. These firms' decrease in sales are offset by an increase in the demand and supply of higher-technology inputs due to the expansion of exporters. Higher supply makes it cheaper to use advanced technologies, and higher demand increases sales of high- relative to low-tech goods. We estimate the model using data on manufacturing plants in Colombia before the trade liberalization and simulate a counterfactual liberalization. Like other unilateral trade liberalizations in developing countries, the skill premium and skill intensity in manufacturing increased, and the size of firms decreased in Colombia. The counterfactual is consistent with these findings, and firms' linkages in the domestic input market are key to explain a widespread increase in technology upgrading and in the demand for skilled labor, despite a contraction in sales.

Keywords: trade liberalization, skill, quality, intermediate inputs, amplification effect.

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International trade is associated with the use of more advanced technologies empirically and theoretically. Since the 1980s, periods of expansion in international trade in developed and developing countries have coincided with increases in demand for skilled workers, in the use of information technology and R&D-intensive equipment, and in investments in innovation and quality improvements. To account for these empirical regularities, economists have proposed several mechanisms through which trade directly affects firms' technology choices—economies of scale, offshoring and trade in capital goods, to name a few.

This paper argues that these direct mechanisms are significantly amplified through firms' linkages in the domestic input market. By shifting production toward importers and exporters and by inducing these firms to upgrade their technology, international trade increases the domestic demand for higher-technology inputs and decreases the cost of adopting new technologies. Firms that use more advanced technologies and produce higher-quality goods are generally stringent in their input purchases. One does not put new wine into old wineskin; one does not make high-quality cars with second rate steel and auto-parts. Automated production processes often also require higher-technology inputs, whose quality is higher and more consistent across batches. On the cost side, the presence of larger, technologically more advanced firms may spur the development of a market for higher-technology inputs, thereby increasing their availability and decreasing their costs. In addition, firms learn from early adopters, and for certain technologies, such as automated processes of procurement and sales, a firm's adoption is only financially viable if other firms in its production chain also adopt. By catalyzing these changes in the domestic market, the reduction of trade barriers may lead to large improvements in technology that reach a much wider set of firms than those directly engaged in international trade.

To formalize this point, we develop a symmetric two-country model where heterogenous firms choose between a backward and an advanced technology. In equilibrium, the least productive firms produce with the backward technology and do not export. More productive non-exporters and all exporters use the advanced technology. If all firms value inputs equally, then trade always leads non-exporters to downgrade technology. In the model, the cost of using the advanced technology is fixed, and the benefit is proportional to operating profit, which for non-exporters, decreases with trade. If, on the other hand, technologically advanced goods can only be made with technologically advanced inputs, then trade has an ambiguous effect on non-exporters' technology. The expansion of exporters increases the domestic demand and supply of high-tech inputs. The increased supply makes the use of advanced technology cheaper, and the increased demand boosts the sales of high- relative to low-tech goods. If these changes are large enough to offset the fall in sales, domestically-oriented firms upgrade their technology and thereby magnify these changes in the domestic input market. Given the theoretical ambiguity on the direction of technical change, we turn to the data.

Our empirical application is the Colombian trade liberalization in 1991. Colombia was one among numerous developing countries that unilaterally liberalized to international trade in the 1980s and 1990s after decades of import-substitution policies. These episodes were followed by broad transformations in manufacturing: Measured productivity, investment, skill intensity, the quality of inputs and of outputs all increased while firm size decreased or remained unchanged. The skill premium typically also rose sharply, by 10% to 20%.[1] Whether existing theoretical mechanisms can account for such puzzlingly large and widespread changes is an open question.

To address this question and to quantify the novel effects of input-output linkages using data, we extend the basic model to a quantitative framework with heterogeneous labor and a continuum of technology choices. More advanced technologies require higher fixed costs of production, they are more intensive in skilled labor and in higher-technology inputs. Economies of scale imply that more productive firms endogenously choose higher technology, become larger, more skill intensive. They sell their output and buy their inputs at higher prices, and they are more likely to engage in international trade due to fixed costs of importing and exporting. Thus, the model provides a unified explanation for well-documented cross-sectional correlations between firms' sales, wages, skill intensity, unit prices, and participation in international trade.[2]

[1]These changes are unlikely to come only from other reforms because they are typically larger in sectors with larger tariff decreases. For productivity changes, see Aw, Roberts and Xu (2011), Eslava et al. (2013), Khandelwal and Topalova (2004), Pavcnik (2002), Trefler (2004) and references there surveyed. Goldberg and Pavcnik (2004, 2007) survey labor market changes, and Tybout (2003) surveys firm size. See Kugler and Verhoogen (2009, 2012), Tovar (2012) and Verhoogen (2008) for quality improvements, and Das et al. (2013) and Holmes and Schmitz (2010) for case studies. The patterns are well-documented for middle-income countries, and they are less clear for low-income countries. The main trade partners of these middle-income countries were at the time high-income countries—not yet China.

[2]See Abowd, Kramarz and Margolis (1999) and Davis and Haltiwanger (1991) for wages, skill and size; Bernard and Jensen (1995, 1997) and Bernard, Jensen, Redding and Schott (2007) for importing and exporting, and Kugler and Verhoogen (2009, 2012) for prices.

The model also brings together many previously proposed direct mechanisms through which trade increases firms' technologies and demand for skills: Exporters upgrade technology if their scale increases or if they face a higher relative demand for technologically-advanced goods abroad as in models of offshoring and of quality differentiation with non-homothetic preferences.[3] Importers upgrade if high-tech Foreign inputs disproportionately lower the cost of producing with higher technology.[4]

We estimate the model using data on a cross-section of manufacturing plants in Colombia in 1988, pre-liberalization. The model replicates well the joint distribution of the firm characteristics above, including moments that corroborate with the assumption that higher-technology firms use more higher-technology inputs. Without this assumption, the domestic input market does not influence technology choices since the relative production cost and demand for high-technology goods cannot change. And without this assumption, a counterfactual trade liberalization induces very minor technological improvements—6% of firms upgrade, 94% downgrade and manufacturing skill intensity increases by only 0.2 percentage points. In contrast, if we assume that high-technology firms disproportionately value high-technology inputs, as the cross-sectional data suggest, then technology upgrades are large and widespread—virtually all importers and exporters and 37% of domestically-oriented firms upgrade, and manufacturing skill intensity increases from 15% to 22%. At the same time, firm size decreases on average by 15% because imports flood the market and we allow for the trade deficit to increase to match its post-liberalization level.

Qualitatively, the counterfactual conforms to 1994 post-liberalization data. Sales decrease, demand for skilled labor increases and large firms increase their sales and skill intensity relative to small firms.[5] Firms that upgrade their technology undergo comprehensive changes—they

[3]See Bustos (2011a) and Helpman et al. (2010, 2012) for the economies of scale hypothesis. Here, differences in wages occur across firms only because of unobservable differences in skill. The demand for skill intensive goods is higher abroad in models of quality-differentiation, e.g. Verhoogen (2008) and Faber (2013), and of offshoring, e.g., Feenstra (2010) and Feenstra and Hanson (1997).

[4]See Burstein, Cravino, Vogel (2013) and Kugler and Verhoogen (2012). We interpret inputs as materials only through most of the paper, but we allow them to include capital inputs in section 6. See also Goldberg et al. (2009, 2010, 2012) for trade in intermediate inputs.

[5]In the counterfactual, we allow for only two parameters to change—one controlling trade deficits and the other controlling non-tariff barriers—to exactly match changes in aggregate imports and exports. Large firms increase their size and skill intensity relative to other firms in Bustos (2011), Kugler and Verhoogen (2012), and Lileeva and Trefler (2010).

invest, become more skill intensive and upgrade the quality of their inputs. At the same time, their profits shrink, a prediction consistent with the strong opposition of industry associations to unilateral trade liberalizations in Colombia and elsewhere.[6] Quantitatively, however, our predictions fall short of the data. Changes in manufacturing skill intensity is similar in the data and in the model, but the counterfactual is obtained under the assumption of inelastic wages, while in the data, the skill premium increased by 11% between 1988 and 1994. A counterfactual with perfectly inelastic wages predicts only a 2.7% rise in the skill premium.

This underprediction is relevant because the model, as explained above, puts together existing mechanisms through which trade increases technology and demand for skilled workers; it magnifies them through firms' input-output linkages, and the counterfactual finds a quantitatively large role for this magnification effect (see section 4). Relative to the literature, we also use data on a much richer set of firm characteristics, such as sales, wages, share of non-production workers, input and output prices, import and export participation and intensities.[7] We are, for example, the first to match the joint distribution of wages and sales, a direct measure of firms' economies of scale. Contradicting previous work, our findings suggest that economies of scale play a minor role in determining technology choices, not least because the correlation between sales and wages is less than 10% in the data. This result explains how, in line with the data, the counterfactual trade liberalization combines large drops in sales, 15% on average, with a large increase in skill intensity, from 15% to 22%.

Still, the novel channel of the interconnection between firms' technology choices through the input market adds analytical and computational complexity, imposing limits on our analysis.

[6]See Edwards (2001) for the politics of the structural reforms in Colombia, and Milgrom and Roberts (1990) for a description of broad firm transformations in modern manufacturing.

[7]Helpman et al. (2014) use export status and wages. Export status may be a good indicator of how well firms compete with foreign firms abroad *and at home*, and it is not clear whether it is the domestic or the foreign market that makes them stand out during a trade liberalization. Another class of models combine firm heterogeneity with cross-sectoral differences, and use mostly aggregate country-sector data. See Burstein and Vogel (2014) and Burstein, Cravino and Vogel (2013) and Parro (2013) use aggregate country-sector data. In these models, there is no within-firm technology changes unless we interpret a firm in the data as a collection of products (firms) in the model and firms drop their least productive product after the trade liberalization. The issue with this interpretation, at least for our Colombian data, is that the number of products per firm increased from 3.6 to 4.4 between 1988 and 1994 and it increased within all sectors. This finding is consistent with technology upgrading in the form of product innovation if one interprets an increase in product scope as a quality upgrade, as in Bernard, et al. (2012) and Goldberg et al. (2010).

We do not address the issues of imperfect labor markets in Helpman et al (2014) or linkages across sectors as in Burstein, Cravino and Vogel (2014) and Parro (2012).[8] The basic model is in section 1 and the quantitative model in section 2. A description of Colombian reforms and the data is in section 3. We estimate the model in section 4 and simulate the trade liberalization in section 5. Section 6 considers other explanations and section 7 concludes.

1 Basic model

The model extends Melitz (2003) to incorporate intermediate goods and endogenous technology choices as in Bustos (2011). Section 1.1 shows that if high- and low-tech firms value inputs equally, then a decrease in trade costs leads domestically-oriented firms to downgrade their technologies because their sales decrease. In section 1.2, we assume that high-tech goods can only be made with high-tech inputs. Then, the effect of trade on domestically-oriented firms' technologies becomes ambiguous because of changes in the input market.

1.1 No specific inputs

There are two symmetric countries, Home and Foreign. We describe the model from Home's perspective. Labor is the only factor of production. The representative consumer sells his endowment of labor L in a competitive market. Wages are the numeraire. Each firm has a differentiated variety and it chooses between a backward technology $\tau = 1$ and an advanced technology $\tau = 2$. We sometimes refer to technologies as types, and write $\omega \in \tau$ when variety ω is of type τ. All varieties are used as final goods and as intermediate inputs for production.

Production There is a large mass of potential entrepreneurs who can pay a fixed cost f_e to enter the market. Upon entry, the firm observes its productivity z drawn from an exogenous distribution G with support $(0, \infty)$, and it chooses whether to exit or to produce. If it produces, it must choose between technologies $\tau \in \{1, 2\}$. Production of technology τ requires a fixed cost

[8] See section 3 and appendix B on cross-sectoral linkages.

f_τ. Once fixed costs are incurred, the production of a firm with productivity z is

$$\tilde{\alpha} z L^{\alpha} X^{1-\alpha} \tag{1}$$

$$\text{where} \quad X = \left[X(1)^{\frac{\sigma-1}{\sigma}} + \Phi^{\frac{1}{\sigma}} X(2)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{2}$$

$$X(\tau) = \left[\int_{\omega\in\tau} x(\omega)^{\frac{\sigma-1}{\sigma}} d\omega\right]^{\frac{\sigma}{\sigma-1}} \quad \text{for } \tau = 1, 2, \tag{3}$$

$\alpha \in (0,1)$ is the weight of labor in production, $\tilde{\alpha} = \alpha^{-\alpha}(1-\alpha)^{-(1-\alpha)}$ is a Cobb-Douglas constant, L is the quantity of labor, and X is a CES aggregate of material inputs. The elasticity of substitution $\sigma > 1$ is the same between and within varieties only to save on notation. Parameter $\Phi > 1$ is a productivity shifter associated with high-tech inputs.

Demand Consumer preferences are represented with CES aggregate X in equation (2). Like firms, the consumer values high-tech goods more, $\Phi > 1$.

International trade After entry, a firm may choose to export by paying an additional fixed cost f_x. There are also per-unit iceberg trade costs: To deliver one unit of a good in the foreign country, $d > 1$ units must be shipped.

Firm behavior The unit cost of labor and material inputs for production is $P^{1-\alpha}$ where

$$P = [P(1)^{1-\sigma} + \Phi P(2)^{1-\sigma}]^{\frac{1}{1-\sigma}},$$

and $P(\tau)$ is the standard CES price index for type-τ goods. The price of a firm with technology parameter z is $\mu P^{\alpha-1}/z$, where $\mu = \frac{\sigma}{\sigma-1}$ is the markup. If the firm does not exit, it has four discrete choices: (i) to produce low-tech and not export, (ii) to produce high-tech and not export, (iii) to export low-tech and (iv) to export high-tech. Net of entry costs, the profit from each of these activities is, respectively:

$$\pi_{H1}(z) = \tilde{\sigma} z^{\sigma-1} P^{\alpha(\sigma-1)} R - f_1$$
$$\pi_{H2}(z) = \Phi \tilde{\sigma} z^{\sigma-1} P^{\alpha(\sigma-1)} R - f_2$$
$$\pi_{x1}(z) = (1 + d^{1-\sigma}) \tilde{\sigma} z^{\sigma-1} P^{\alpha(\sigma-1)} R - (f_1 + f_x)$$
$$\pi_{x2}(z) = \Phi(1 + d^{1-\sigma}) \tilde{\sigma} z^{\sigma-1} P^{\alpha(\sigma-1)} R - (f_2 + f_x).$$

where $\tilde{\sigma} = \sigma^{-\sigma}(\sigma - 1)^{\sigma-1}$ is a constant and $R = \frac{\sigma L}{1+\alpha(\sigma-1)}$ is domestic absorption—consumer spending L is scaled up to account for firms' demand for inputs.[9] Technology upgrading increases operating profits by a factor of Φ and exporting increases it by $(1 + d^{1-\sigma})$. Because our focus is on non-exporters, we analyze an equilibrium where some of these firms produce high-tech, as illustrated in figure 1. There are three cutoffs $z_1 < z_2 < z_x$. Firms with productivity below z_1 exit; firms with productivity $z \in [z_1, z_2)$ produce low-tech goods and do not export; firms with productivity $z \in [z_2, z_x)$ produce high-tech goods and do not export, and firms with productivity $z > z_x$ produce high-tech and export. Such an equilibrium holds if and only if (appendix A)

$$\Phi f_1 < f_2 \quad \text{and} \quad \Phi(f_2 - f_1) < f_x(\Phi - 1)d^{\sigma-1}.$$

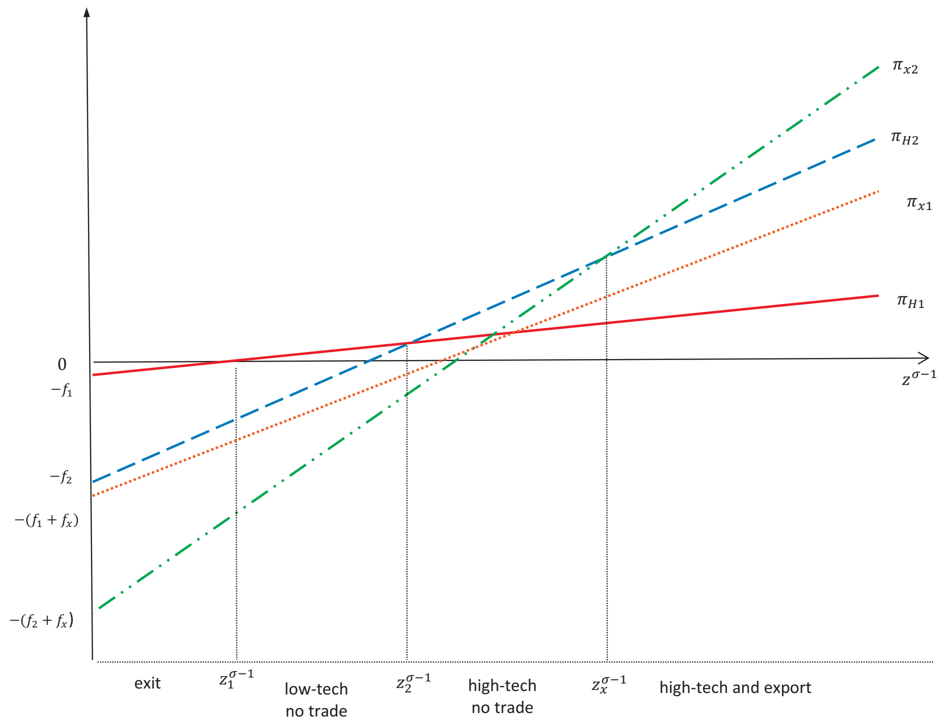
The fixed cost of producing high-tech is sufficiently high, and trade costs f_x and d are high relative to the difference between the fixed cost of producing high- and low-tech goods $(f_2 - f_1)$.

Equilibrium An equilibrium is described by a mass of entrants M_e and productivity cutoffs z_1, z_2 and z_x. The price index as a function of these equilibrium variables is:

$$P = \left\{ \mu^{1-\sigma} M_e \left[\int_{z_1}^{z_2} z^{\sigma-1} dG(z) + \Phi \int_{z_2}^{\infty} z^{\sigma-1} dG(z) + \Phi d^{1-\sigma} \int_{z_x}^{\infty} z^{\sigma-1} dG(z) \right] \right\}^{\frac{1}{\alpha(1-\sigma)}}.$$

[9] The expression for absorption comes from rearranging $R = L + [(1 - \alpha)/\mu]R$.

Figure 1: Exporting and technology choices



Equilibrium conditions are four: (i) Expected profits are zero,

$$f_e = \int_{z_1}^{z_2} \pi_{H1}(z)dG(z) + \int_{z_2}^{z_x} \pi_{H2}(z)dG(z) + \int_{z_x}^{\infty} \pi_{x2}(z)dG(z).$$

(ii) At z_1, firms are indifferent between exiting and entering, $\pi_{H1}(z_1) = 0$. (iii) At z_2, firms are indifferent between upgrading technologies or not, $\pi_{H1}(z_2) = \pi_{H2}(z_2)$. (iv) At z_x, high-tech firms are indifferent between exporting or not, $\pi_{H2}(z_x) = \pi_{x2}(z_x)$.

Trade liberalization Consider a decrease in trade costs d or f. As in Melitz (2003), we show in appendix A that the price index P must decrease for the equilibrium to be restored—otherwise, the free-entry condition would be violated. Rearranging equilibrium condition (iii), $\pi_{H1}(z_2) = \pi_{H2}(z_2)$, yields

$$z_2 = \left[\frac{f_2 - f_1}{\tilde{\sigma}(\Phi - 1)R}\right]^{\frac{1}{\sigma-1}} P^{-\alpha}. \tag{4}$$

Since the term in bracket is exogenous, the cutoff z_2 must increase. That is, *when inputs are not specific, trade leads domestically-oriented firms to downgrade their technologies.*

1.2 Specific inputs

The setting is exactly as above except for the production function (1), where we now assume that high-tech goods can only be made with high-tech inputs. After incurring the fixed costs, the output of a firm with technology τ is

$$\begin{aligned} &\tilde{\alpha} z L^{\alpha} X^{1-\alpha} && \text{if } \tau = 1 \\ &\tilde{\alpha} z L^{\alpha} X(2)^{1-\alpha} && \text{if } \tau = 2 \end{aligned}$$

where X and $X(2)$ are defined in equations (2) and (3) above.[10]

Firm behavior The revenue of a firm of type τ and price p is

$$\begin{aligned} & r(p,\tau) = p^{1-\sigma}\chi(\tau) \qquad (5) \\ \text{where} \quad & \chi(1) = P^{\sigma-1}\left[L + \frac{1-\alpha}{\mu}R(1)\right] \\ & \chi(2) = \Phi\chi(1) + \frac{1-\alpha}{\mu}P(2)^{\sigma-1}R(2) \end{aligned}$$

and $R(\tau)$ is total absorption of goods of type τ. Function $\chi(\tau)$ is an endogenous demand shifter associated with producing with technology τ. Low-tech firms face demand from consumers, with spending L, and from low-tech firms with spending $\left[\frac{1-\alpha}{\mu}R(1)\right]$. High-tech firms face an additional demand from other high-tech firms with spending $\left[\frac{1-\alpha}{\mu}R(2)\right]$. Integrating both sides of equation (5) when $\tau = 1$ and rearranging, we get absorption

$$R(1) = \frac{\sigma[P(1)/P]^{1-\sigma}}{\sigma - (1-\alpha)(\sigma-1)[P(1)/P]^{1-\sigma}}L,$$

and $R(2) = R - R(1)$, where $R = \frac{\sigma L}{1+\alpha(\sigma-1)}$ is total absorption as before. Absorption of low-tech goods $R(1)$ decreases in their relative prices $P(1)/P$. The unit cost of labor and material inputs is $P^{1-\alpha}$ for low-tech firms and $P(2)^{1-\alpha}$ for high-tech firms. If a firm does not exit, its profit for

[10] The assumption that low-tech goods aggregate materials in the same manner that consumers aggregate goods is not necessary as long as the consumer attributes some value to low-tech goods.

each of the four discrete choices is

$$\pi_{H1}(z) = \tilde{\sigma} z^{\sigma-1} P^{(1-\alpha)(\sigma-1)} \chi(1) - f_1$$
$$\pi_{H2}(z) = \tilde{\sigma} z^{\sigma-1} P(2)^{(1-\alpha)(1-\sigma)} \chi(2) - f_2$$
$$\pi_{x1}(z) = (1 + d^{1-\sigma}) \tilde{\sigma} z^{\sigma-1} P^{(1-\alpha)(\sigma-1)} \chi(1) - (f_1 + f_x)$$
$$\pi_{x2}(z) = (1 + d^{1-\sigma}) \tilde{\sigma} z^{\sigma-1} P(2)^{(1-\alpha)(1-\sigma)} \chi(2) - (f_2 + f_x).$$

Exporting still increases operating profits by a factor of $(1+d^{1-\sigma})$, but the benefit of technology upgrading is now endogenous. As the availability of high-tech goods increases, it becomes relatively cheaper to produce them, $\frac{P(2)}{P}$ decreases, and the relative demand for high-tech $\frac{\chi(2)}{\chi(1)}$ increases. Profits π_{H2} and π_{x2} then increase relative to π_{H1} and π_{x1}.

Equilibrium We again focus on an equilibrium where some domestic firms produce high-tech. There are three cutoffs, $z_1 < z_2 < z_x$ as illustrated in figure 1. An equilibrium is described by M_e, z_1, z_2 and z_x satisfying the same conditions (i)-(iv) as before.[11]

Trade liberalization A decrease in trade costs d or f_x now has an ambiguous effect on cutoff z_2. Rearranging equilibrium condition (iii), $\pi_{H1}(z_2) = \pi_{H2}(z_2)$, domestic firms upgrade their technology if

$$\underbrace{\left\{ \Phi \left[\frac{P(2)}{P} \right]^{(1-\alpha)(1-\sigma)} - 1 \right\} P^{\alpha(\sigma-1)} \left[L + \frac{1-\alpha}{\mu} R(1) \right]}_{\text{market for final goods and inputs for low-tech firms}} + \underbrace{\frac{(1-\alpha)}{\mu} P(2)^{\alpha(\sigma-1)} R(2)}_{\text{market for inputs for high-tech firms}} \qquad (6)$$

increases and z_2 decreases. There are opposing forces in both markets. In the market for final goods and inputs from low-tech firms, the term in curly brackets generally increases because the relative cost of producing high-tech $P(2)/P$ decreases with the exit of low-tech domestic firms and the greater availability of high-tech Foreign inputs. The demand shifter

[11] The expressions for prices as a function of equilibrium variables are in appendix A.4. The conditions for such an equilibrium to exist are not in closed form and appear in appendix A.3. With specific inputs, there is always an equilibrium where all firms produce the low-tech good, and the cost of producing high-tech is infinite. In the quantitative model below, this equilibrium is eliminated because we allow all firms to use all inputs, only their relative efficiencies change. Multiple equilibria may still arise, but that does not seem to be the case for the parameter estimates. See appendix E.

$P^{\alpha(\sigma-1)}\left[L+\frac{1-\alpha}{\mu}R(1)\right]$, however, tends to decrease—market tightens (P decreases) and spending of low-tech firms on materials falls ($R(1)$ decreases). In the market for high-tech inputs, the decrease in production costs is more than offset by market tightening ($P(2)^{\alpha(\sigma-1)}$ decreases), but the market increases as exporters expand ($R(2)$ increases). It is not difficult to generate numerical examples where both terms in equation (6) increase.[12]

Discussion Our claim is not one of generality. We have established the theoretical possibility for changes in the domestic input market to lead firms to upgrade their technologies. We now develop a quantitative model to assess whether these effects are significant. A few differences in the quantitative model are worth highlighting. There is a continuum of technology levels and all firms, including exporters, may upgrade their technologies with the trade liberalization. Upgrades among exporters amplify the effects of the domestic input market described above—the relative cost of producing high-tech decreases and the demand for high-tech inputs increase further. Exporters themselves benefit from these changes. Firms pay a fixed cost to import inputs. The behavior of importers and their effect on local input markets are analogous to exporters'. We allow higher technology goods to be more skill intensive. So trade, changes the demand for skilled labor through across-firm reallocation and within-firm technology changes.

2 Quantitative model

There are two countries, Home and Foreign. Home (Colombia in our empirical application) is a small developing country. Foreign variables, denoted with an asterisk, are exogenous. We allow Foreign to supply higher-tech goods and to have a higher relative demand for high-tech goods than Home. Differences in demand may arise from non-homothetic preferences or from high-tech Foreign firms, as in Antràs, Garricano and Rossi-Hansberg (2006) and Feenstra and Hanson (1997). There are two types of labor, skilled and unskilled. As before, a representative consumer sells labor in a competitive market and maximizes CES preferences. There is monopolistic

[12]The discussion here surrounds a typical case, but none of the movements above are unambiguous. For example, if technology downgrading by non-exporters offset the expansion of exporters, $P(2)/P(1)$ decreases and $R(1)/R(2)$ increases.

competition among firms that differ in their exogenous productivity z and their endogenous technology τ.

The focus of our empirical analysis is the medium-run, the five years in which arguably most of the changes in the Colombian labor market occur. During the period, imports increased faster than exports in Colombia as it is typical with unilateral trade liberalizations. Average sales decreased and there was some exit—a change inconsistent with free entry and constant markups, where average sales must increase whenever the probability of surviving decreases. We view free entry and balanced trade as long-run tendencies. In 1999, nearly ten years after the liberalization, a large devaluation of Colombian pesos increased exports and probably firm size. But to study the medium run, we allow for unbalanced trade and take the set of potentially active firms as exogenous. Exit may occur since there is a fixed cost of production. These assumptions make it harder for trade to increase technologies and the demand for skills in the model since sales are allowed to drop and there are economies of scale in the production of high-tech goods. We reintroduce free entry as a robustness check in section 6.

Production We generalize the production set up of section 1.2 to a continuum of technologies τ and to two types of labor. Each firm ω has a differentiated variety and it chooses technology $\tau \in \mathbb{R}_+$. A low τ represents low technologies. All goods have final and intermediate usage, and all firms use skilled and unskilled labor, and material inputs for production. The fixed cost of producing type τ is $f(\tau)$, where f is continuous and increasing. After incurring this cost, the output of firm ω when producing type τ is

$$\tilde{\alpha} z(\tau, \omega) L(\tau)^{\alpha} X(\tau)^{1-\alpha} \tag{7}$$

$$\text{where} \quad L(\tau) = \left[\sum_{\varsigma \in \{s,u\}} l_{\varsigma}^{(\sigma_L - 1)/\sigma_L} \Phi_L(\varsigma, \tau)^{1/\sigma_L} \right]^{\sigma_L/(\sigma_L - 1)}, \tag{8}$$

$$X(\tau) = \left[\int x(\omega')^{(\sigma-1)/\sigma} \Phi[\tau(\omega'), \tau]^{1/\sigma} d\omega' \right]^{\sigma/(\sigma-1)}, \tag{9}$$

$\alpha \in (0, 1)$, $\tilde{\alpha} = \alpha^{-\alpha}(1-\alpha)^{-(1-\alpha)}$, $z(\tau, \omega)$ is a firm- and technology-specific productivity parameter, l_{ς} is the quantity of labor of skill $\varsigma \in \{s, u\}$, $x(\omega')$ is the quantity of input variety ω', and

$\Phi : (\mathbb{R}_+ \times \mathbb{R}_+) \to \mathbb{R}_+$ and $\Phi_L : (\{s, u\} \times \mathbb{R}_+) \to \mathbb{R}_+$ are productivity shifters.

Production is a Cobb-Douglas function of labor $L(\tau)$ and material inputs $X(\tau)$. Function $L(\tau)$ is a CES aggregate of skilled and unskilled labor. Denote with w_s and w_u the wages of skilled and unskilled labor. Then, the firm's demand for skilled relative to unskilled workers is

$$\frac{l_s}{l_u} = \left(\frac{w_s}{w_u}\right)^{-\sigma_L} \frac{\Phi_L(s,\tau)}{\Phi_L(u,\tau)}. \tag{10}$$

Skill intensity decreases in the skill premium $\frac{w_s}{w_u}$ and increases in technology if $\frac{\Phi_L(s,\tau)}{\Phi_L(u,\tau)}$ is increasing in τ. Section 4 below estimates the ratio $\frac{\Phi_L(s,\tau)}{\Phi_L(u,\tau)}$ as a function of τ.

Function $X(\tau)$ is the CES aggregate of material inputs. Assume the productivity shifter $\Phi(\tau', \tau)$ of an input of technology τ' when the output technology is τ is

$$\Phi(\tau', \tau) = \frac{\exp(\tau' - \tau)}{1 + \exp(\tau' - \tau)} \tag{11}$$

Function Φ, the cumulative distribution function of a logistic random variable, has three key properties: It is increasing in the first argument and decreasing in the second. Higher-tech inputs are more efficient, and higher-tech output is more difficult to produce. It is also log-supermodular. The firm's relative demand for any two inputs 1 and 2 of types $\tau_1 > \tau_2$,

$$\frac{x(1)}{x(2)} = \left(\frac{p_1}{p_2}\right)^{-\sigma} \frac{\Phi(\tau_1, \tau)}{\Phi(\tau_2, \tau)}, \tag{12}$$

is increasing in output type τ—higher-tech firms demand relatively more high-tech inputs.[13]

Demand As in section 1, the representative consumer aggregates goods in the same fashion as low-tech firms. Preferences are represented by $X(0)$ defined in equation (9).

[13]Function Φ is log-supermodular if $\frac{\partial^2 \ln \Phi(\tau', \tau)}{\partial \tau' \partial \tau} > 0$, or equivalently, $\frac{\Phi(\tau_1, \tau)}{\Phi(\tau_2, \tau)}$ is increasing in τ whenever $\tau_1 > \tau_2$. See Costinot (2009).

International Trade To access Foreign varieties, firm ω incurs a fixed cost $f_M(\omega)$.[14] If Foreign goods have higher technologies, as the parameter estimates below suggest, then higher-tech firms gain more from importing. Firm ω must also incur a fixed cost $f_X(\omega)$ to access the Foreign market with demand

$$r^*(\tau, p) = p^{1-\sigma}\Phi(\tau, \mathrm{T}^*)Y^*. \tag{13}$$

Parameter $Y^* > 0$ captures the size of the Foreign market, while parameter T^* captures the relative demand of high- to low-tech goods. Since Φ is log-supermodular, for any two goods 1 and 2 with $\tau_1 > \tau_2$, Foreign demand relative to Home consumer demand is

$$\left[\frac{r^*(\tau_1, p_1)}{r^*(\tau_2, p_2)}\right] \Big/ \left[\frac{r_c(\tau_1, p_1)}{r_c(\tau_2, p_2)}\right] = \left[\frac{\Phi(\tau_1, \mathrm{T}^*)}{\Phi(\tau_2, \mathrm{T}^*)}\right] \Big/ \left[\frac{\Phi(\tau_1, 0)}{\Phi(\tau_2, 0)}\right] > 1 \quad \text{if } \mathrm{T}^* > 0.$$

Higher-tech firms are then more likely to export. The fixed costs of importing and exporting imply that larger, more productive firms are also more likely to trade. We allow these costs $f_X(\omega)$ and $f_M(\omega)$ to be firm-specific because participation in trade varies across firms with similar characteristics in the data.

The firm's problem The CES cost of labor and material inputs for production depends on a firm's output technology through shifters Φ_L and Φ. Let Ω and Ω^* be the sets of domestic and foreign varieties, respectively, and define price indices:

$$P(\tau) = \left[\int_{\Omega} p(\omega)^{1-\sigma}\Phi(\tau(\omega), \tau)d\omega\right]^{1/(1-\sigma)} \quad \text{and} \quad P^*(\tau) = \left[\int_{\Omega^*} p(\omega)^{1-\sigma}\Phi(\tau(\omega), \tau)d\omega\right]^{1/(1-\sigma)}$$

[14] Consumers do not pay a fixed cost to access the same goods as importing firms. This asymmetry can be eliminated by assuming all firms and consumers can access foreign goods by paying an additional per-unit distribution cost. Firms may pay a fixed cost to forgo these distribution costs.

A bundle of labor and material inputs for producing type τ with import status 1_M costs

$$C(\tau, 1_M) = w(\tau)^\alpha P(\tau, 1_M)^{1-\alpha},$$
$$\text{where} \quad w(\tau) = \left[\sum_{\varsigma=s,u} w_\varsigma^{(1-\sigma_L)} \Phi_L(\varsigma, \tau)\right]^{1/(1-\sigma_L)},$$
$$P(\tau, 1_M) = \left[P(\tau)^{1-\sigma} + 1_M P^*(\tau)^{1-\sigma}\right]^{1/(1-\sigma)}$$

are the CES prices of labor and material. Firm ω's demand for labor of skill $\varsigma \in \{u, s\}$ is

$$l_\varsigma(\omega) = \left(\frac{w_\varsigma}{w(\tau)}\right)^{\sigma_L} \Phi_L(\varsigma, \tau) \left[\frac{\alpha}{\mu} r_T(\omega)\right]$$

where $\mu = \frac{\sigma}{\sigma-1}$ is the markup and $r_T(\omega)$ is the firm's total revenue. Aggregating over consumers and firms, spending on a variety with price p and type τ in Home is

$$r(\tau, p) = p^{1-\sigma}\chi(\tau) \tag{14}$$
$$\text{where} \quad \chi(\tau) = \Phi(\tau, 0)P(0, 1)^{\sigma-1}Y + \int_\Omega \Phi[\tau, \tau(\omega)]P[\tau(\omega), 1_M(\omega)]^{\sigma-1}\left(\frac{1-\alpha}{\mu}\right) r_T(\omega)d\omega.$$

As in section 1, function $\chi(\tau)$ summarizes the country-wide demand for technology τ: Each type of spending, consumers' Y and firms' $\frac{1-\alpha}{\mu} r_T$, is weighted by its own relative demand for type τ captured by price indices P and shifters Φ. Firm ω sets price $p = \mu C(\tau, 1_M)/z(\tau, \omega)$ and chooses technology τ, entry 1_E, import status 1_M and export status 1_X to maximize profits:

$$\pi(\omega) = \max_{\tau, 1_E, 1_M, 1_X} 1_E \left\{\sigma^{-1}\left[r(\tau, p) + 1_X r^*(\tau, p)\right] - \left[f(\tau, \omega) + 1_M f_M(\omega) + 1_X f_X(\omega)\right]\right\}. \tag{15}$$

A firm's operating profit $\sigma^{-1}\left[r(\tau, p) + 1_X r^*(\tau, p)\right]$ is proportional to its productivity z and the cost of producing higher technology $f(\tau)$ is fixed. So, more productive firms endogenously choose higher technology. The decisions of technology, import and export statuses cannot be disentangled. Exporting increases the scale of production rendering imports more profitable, and importing decreases variable costs rendering exports more profitable. Importing and exporting also yield higher profits from technology upgrading. As in section 1, there are external economies of scale—a large mass of high-tech firms decreases the relative cost $P(\tau)$ of high-tech material inputs and increase the relative demand for them $\chi(\tau)$.

Tariffs, trade and equilibrium Price $p(\omega)$ that agents at Home pay for Foreign varieties $\omega \in \Omega^*$ includes an *ad valorem* tariff τ: $p(\omega) = (1+\tau)p^*(\omega)$ where $p^*(\omega)$ is the unit price after trade costs.[15] Home's imports from Foreign is $R_{HF} = R^\tau_{HF}/(1+\tau)$ where R^τ_{HF} is after-tariff spending on Foreign goods,

$$R^\tau_{HF} = \left[\frac{P^*(0)}{P(0,1)}\right]^{1-\sigma} Y + \int_\Omega 1_M(\omega) \left\{\frac{P^*[\tau(\omega)]}{P[\tau(\omega),1]}\right\}^{1-\sigma} \frac{1-\alpha}{\mu} r_T(\omega) d\omega.$$

Tariff revenues $T = \tau R_{HF}$ are redistributed to consumers through a lump sum transfer. Home's exports to Foreign are

$$R_{FH} = \int_\Omega 1_X(\omega) r^*[\tau(\omega), p(\omega)] d\omega.$$

To close the model, we take a stance on the factor(s) used for fixed costs f, f_M and f_X. The data do not distinguish fixed from variable production costs, and we assume that fixed costs use a separate factor (labor or capital) that differs from the skilled and unskilled labor used in production function (7). When matching the model to data in section 4 below, we then take variable labor $\frac{l_s(\omega)}{l_s(\omega)+l_u(\omega)}$ to be firm ω's skill intensity, and in the counterfactuals, we assume that the supply of the factor used in fixed costs is perfectly elastic so that fixed costs do not change.[16] Without loss of generality, let its price be one so that f, f_M and f_X are the costs and technologies to produce, to import and to export. Let D_H be Home's exogenous trade deficit, $L_s(w)$ and $L_u(w)$ be the supply of skilled and unskilled labor when wages are $w = (w_s, w_u)$. Then, consumer spending is

$$Y = w_s L_s(w) + w_u L_u(w) + F + \int_\Omega \pi(\omega) d\omega + T + D_H \tag{16}$$
$$\text{where } F = \int_\Omega 1_E(\omega) \left[f(\tau(\omega)) + 1_M(\omega) f_M(\omega) + 1_X(\omega) f_X(\omega)\right] d\omega$$

[15] We make the standard assumption that Foreign factors are used to transport Foreign goods.

[16] This assumption is irrelevant when labor is perfectly elastic. In appendix **??**, the results barely change when we let fixed costs change with wages in the case of inelastic labor supply.

is overall spending on fixed costs. By Walras' law, $R_{HF} = R_{FH} + D_H$. Labor markets clear if

$$L_\varsigma(w) = \int_\Omega l_\varsigma(\omega) d\omega \qquad \text{for } \varsigma = s, u. \tag{17}$$

To summarize, an economy is defined by Home's labor supply $L_s(w)$ and $L_u(w)$, fixed production cost $f(\tau)$, tariff τ, deficit D_H, and the set of firms Ω each with its productivity $z(\tau, \omega)$ and fixed cost of importing $f_M(\omega)$ and of exporting $f_X(\omega)$. Foreign is described by demand shifters T^* and Y^*, and set of goods Ω^* each with its price $p^*(\omega)$ and type $\tau(\omega)$. An equilibrium is a set of wages (w_u, w_s) that clears the labor market.

2.1 Model without specific inputs

As in section 1, the only difference between the model with and without specific inputs is the valuation of intermediate inputs in production. After incurring fixed costs, assume production in equation (7) is

$$\tilde{\alpha} z(\tau, \omega) L(\tau)^\alpha X(0)^{1-\alpha}.$$

That is, a firm's valuation of material inputs does not depend on its technology choice. Spending on a variety with price p and type τ in Home is now

$$r(\tau, p) = p^{1-\sigma} \chi(\tau) \tag{18}$$

$$\text{where} \quad \chi(\tau) = \Phi(\tau, 0) \left[P(1)^{\sigma-1} Y + \left(\frac{1-\alpha}{\mu} \right) \int_{\omega \in \Omega} P(1_M(\omega))^{\sigma-1} r_T(\omega) d\omega \right],$$

$$P(1_M) = \left[\int_{\Omega \bigcup 1_M \Omega^*} p(\omega)^{1-\sigma} \Phi(\tau(\omega), 0) d\omega \right]^{1/(1-\sigma)} \tag{19}$$

is the price index of a firm with import status 1_M. Type τ only enters demand through shifter $\Phi(\tau, 0)$, which is now common for all firms and consumers. If all firms import, demand is further simplified to $r(\tau, p) = \Phi(\tau, 0) \left[\frac{p}{P(1)} \right]^{1-\sigma} R$, where R is total absorption. We henceforth refer to this model as the NSI (non-specific-inputs) model, and to the model where the different types of output require different types of inputs above as the SI (specific-inputs) model.

The main result from the basic model of section 1 still holds: Trade has a negative effect on the technology of domestically-oriented firms in the NSI model and an ambiguous effect in the SI model. But the quantitative model renders possible the use of data on a rich set of firm characteristics—sales, import and export participation and intensity, prices, wages, and skill intensity—to further exploit the qualitative and quantitative implications of the two models regarding the cross-section and the effects of trade.[17]

3 Data and the Colombian Trade Liberalization

Following international trends, Colombia significantly reduced trade barriers in a broad set of industries between 1985 and 1991 after decades of import-substitution policies.[18] Non-tariff barriers, which affected 99.6% of industries in 1984, were removed, and the average tariff in manufacturing decreased from 50% to 13%. Figure 2 shows the evolution of effective tariff rates between 1984 and 1996. The sharp fall in 1991 was arguably unexpected. In 1990, the newly-elected Gaviria administration designed a four-year plan to reduce trade barriers, but it abruptly implemented the whole plan after a few months under the impression that uncertainty was holding back changes in firms.

We use the Colombian Annual Manufacturing Survey which comprises all manufacturing plants in Colombia with 10 or more workers. A plant is interpreted as a firm in the model.[19] We use two sample years. We estimate the model with 1988 pre-liberalization data and compare the counterfactual results to 1994 post-liberalization data. For each plant in 1988, the data contain

[17] It is fairly straightforward to provide a theoretical formulation that nests these two models. For example, one could re-define Φ in equation (11) as

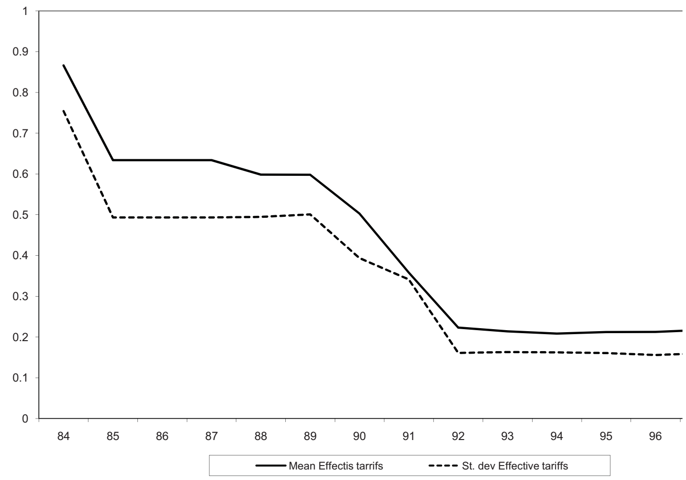
$$\Phi(\tau', \tau) = \frac{\exp(\tau' - \phi\tau)}{1 + \exp(\tau' - \phi\tau)}$$

where parameter $\phi > 0$ governs the complementarity between inputs and output. But to keep our estimation simpler, we estimate the model with $\phi = 0$ (NSI model) and $\phi = 1$ (SI model), and we show that the SI model predicts reasonably well out-of-sample moments that reflect complementarity between inputs and output. An alternative approach would be to use these out-of-sample moments to estimate a complementarity parameter ϕ.

[18] Attanasio et al (2004) and Edwards (2001) describe reforms in Colombia. The trade liberalization was accompanied by reforms in the labor and financial markets, but these were less comprehensive because they stalled for political reasons. See also Lora (2001).

[19] Plants report whether they belong to a firm with multiple plants, but not the plant(s) to which they are linked. Six percent of plants are from multi-plant firms, and moments in the data look similar if these plants are excluded.

Figure 2: Effective tariffs, 1984-1996 (source: Eslava et al. (2013))



the value of domestic and export sales, and spending on domestic and imported materials. The number of workers and wage bill are reported separately for managers, technicians and production workers. We take managers and technicians to be white-collar workers, but below, measurement error distinguishes them from unobservable skilled workers.

The survey changed during the years of interest. In 1994, there is no plant-specific data on imports and exports. We use only total manufacturing imports and exports from Feenstra et al. (2005). Plant identification numbers changed in 1990. So, we cannot infer exit or within-firm changes.[20] Our measure of white-collar workers is not available after 1994 because the classification of employees changed in 1995.

Throughout, we aggregate all manufacturing plants disregarding sectoral classifications. This approach is reasonable in our data because the observable market conditions faced by firms in different sectors that potentially source inputs from different sectors are similar. In particular, in line with the literature, appendix B shows that, in the 1988 cross-section, (i) xx% of variations in firm-characteristics occur within sectors, (ii) the correlations that we exploit in the aggregate data occur systematically within sectors. The trade liberalization was also broad enough to affect all sectors. Between 1988-1994, (iii) xx% of changes in firm characteristics occurred

[20] The number of firms decreases slightly in 1991, but there is a long term trend in increasing number of firms as the economy grows, making it hard to quantify exit.

within sectors and (iv) sectors experienced similar systematic changes.[21]

4 Pre-liberalization cross-section

We estimate the model in three stages using the method of simulated moments. The first stage in section 4.1 estimates parameters associated with technology choices and international trade. The second and third stages in sections 4.2 and 4.3 estimate parameters associated with skill intensity and with prices, respectively. With these latter estimates, we use out-of-sample moments to illustrate that the SI model captures well features of the data that reflect systematic patterns in firms' material purchases, patterns which the NSI model rules out by assumption.

4.1 Stage 1: Technology choices

The estimation procedure is in section 4.1.1. There are 38 moments, 12 parameters in the SI model and 11 parameters in the SI model. We describe the parametrization, simulation and moments, and discuss parameter identification. Section 4.1.2 contains the results.

4.1.1 Stage 1: Estimation procedure

Parametrization In order to estimate parameters associated with technology choices and not parameters associated with labor—$\Phi_L(s,\tau)$, $\Phi_L(u,\tau)$ and wages—we make two assumptions that are justified by the parametrization and results of stage 2: (i) the CES cost of labor $w(\tau) = 1$ for all choices τ, and (ii) higher technology firms hire relatively more skilled workers so that the rankings of firms' average wage and technology coincide. Assumption (i) is without

[21] Using data from Brazil that spans a trade liberalization, Helpman et al.'s (2012) estimate that within sector variation accounts for 80% of inequality in the cross-section and over 70% of changes in inequality. See also Bernard, Eaton, Jensen and Kortum (2003) for other firm characteristics. Caliendo and Parro (2014) use data on input-output matrices to analyze the effects of NAFTA and show that increasing the labor share of inputs dramatically decreases the effects of trade, consistent with our findings in section 6. Caliend and Parro do not show how the differences in tariff decreases across sectors affect upstream or downstream sectors differentially. There are also data constraints. Sectoral categories in input-output matrices are very coarse, and Raveh and Reshef (2004) find that imports of R&D intensive capital is associated with increased skill premium across countries, but not aggregate imports of capital. In a previous version of this paper, we obtain very similar results using data on individual sectors (Fieler, Eslava and Xu (2014)).

Table 1: List of parameters of stage 1

description	model variable	parametrization	parameter
firm productivity	$z(\tau,\omega)$	$z_1(\omega)+z_2(\omega)\tau$	
		$z_1 \sim$ log-normal	μ_1, σ_1
		$z_2 \sim$ normal with mean 0	σ_2
fixed cost of production, SI model	$f(\tau)$	$= f_1 + f_2\tau$	f_1, f_2
NSI model		$= f_1 + f_2\tau^{10}$	
fixed cost of importing	$f_M(\omega)$	$\sim$ log-normal	μ_M, σ_M
fixed cost of exporting	$f_X(\omega)$	$\sim$ log-normal	μ_X, σ_X
ref. technology of Foreign demand			T^*
size of Foreign market			Y^*
Technology of Foreign firms (SI model)			τ^*

Fixed parameters are $Y = p^* = 1$, $\sigma = 5$, $\alpha = 0.7$, $\tau = 0.277$, $w(\tau) = 1$ for all τ.

loss of generality—given the Cobb-Douglas production function, the overall productivity of labor can be factored out into the productivity parameters $z(\tau,\omega)$. It allows us to disentangle technology choices from the demand for skilled versus unskilled workers governed by the ratio $\frac{\Phi_L(s,\tau)}{\Phi_L(u,\tau)}$. Assumption (ii) allows for the identification of the two dimensions of firm productivity in $z(\tau,\omega)$—its overall level, and how productivity changes with τ.

We make additional normalizations and fix parameters that are not identified. We set consumer income $Y = 1$ as a way of normalizing the size of the labor force. We assume that all Foreign goods have the same price and technologies and set $p^* = 1$ for all $\omega \in \Omega^*$. Setting $p^* = 1$ fixes the units with which final goods are measured.[22] We set $\tau^* = 0$ in the NSI model where the technology of Foreign goods is irrelevant. The elasticity of substitution across goods σ is not separately identified from $z(\tau,\omega)$ since it enters only as an exponent of $z(\tau,\omega)$ in demand. We take $\sigma = 5$ from Broda and Weinstein (2006) and experiment with other values in appendix **??**. The average tariff on manufactures in 1988 Colombia is $\tau = 27.7\%$ and the labor share is $\alpha = 0.7$.

We parameterize technologies $z(\tau,\omega)$, fixed costs $f(\tau)$, $f_M(\omega)$ and $f_X(\omega)$. The fixed costs of international trade are log-normally distributed with parameters μ_M and σ_M for importing

[22]We do not match number of employees or sales in dollars or Colombian pesos, but sales relative to absorption. Doubling Y in the model would double the size of the labor force L, double sales and absorption, but not change sales relative to absorption. If we doubled p^* and made all Home firms half as productive, the model's predictions would not change either.

costs $f_M(\omega)$ and parameters μ_X and σ_X for exporting costs $f_X(\omega)$. Let

$$z(\tau,\omega) = \max\{0, z_1(\omega) + z_2(\omega)\tau\} \tag{20}$$

where $z_1(\omega)$ is independently drawn from a log-normal distribution with mean parameter μ_1 and variance parameter σ_1, and $z_2(\omega)$ is drawn from a normal with mean zero and variance σ_2. We allow the rate at which productivity changes with technology to be firm-specific because the model would otherwise predict a perfect correlation between sales and wages.[23] Let

$$f(\tau) = f_1 + f_2\tau \qquad \text{SI model}$$

$$f(\tau) = f_1 + f_2\tau^{f_3} \qquad \text{NSI model}$$

where $f_1 \geq 0$, $f_2 \geq 0$ are parameters to be estimated and we fix $f_3 > 0$. Fixed costs are linear in the SI model where firms' technology choices are naturally constrained by the lack of availability of high-tech inputs. In the NSI model, we add parameter f_3 because firms with positive technology draws $z_2(\omega)$ choose infinite technology if the fixed cost of production is not sufficiently convex. We set $f_3 = 10$ here and show in appendix D that results don't change if $f_3 \in \{7, 15\}$. Other estimated parameters are Foreign's demand shifters T^* and Y^*, and the technology of Foreign goods τ^* in the SI model. Table 1 summarizes the parameters.

Stage 1 simulation We simulate the behavior of 5000 firms. Each firm has a fixed vector of four independent standard normal random variables. For each parameter guess, we transform these vectors to get firm-specific productivity parameters $z_1(\omega)$ and $z_2(\omega)$, fixed costs $f_X(\omega)$ and $f_M(\omega)$. Firms may exit or enter the market. If they enter, they choose a technology level from a grid with 200 choices $\tau \in [0, 10]$. Together with the four choices on participation of international trade—to import only, to export only, to import and export, or to do neither—firms have 801 discrete choices over which we iterate.[24]

Given firms' discrete choices, the vector of price indices $P(\tau)$ is a fixed point calculated

[23] Analogous two dimensions of heterogeneity appear in Hallak and Sivadasan (2013).

[24] Our results are robust to increasing the number of firms and technology choices. See appendix E.

Table 2: List of moments

	# of moments
• 10%, 25%, 50%, 75%, 90% of the unconditional distribution of log(normalized domestic sales)	5
• By quartile of domestic sales, ...	
... share of plants exporting	4
... share of plants importing	4
... average spending on imported inputs/total spending on materials	4
... average export sales/total sales	4
• % of firms in the n^{th} quartile of domestic sales and the m^{th} quartile of wages for $n, m = 1, ..., 4$	16
• share of firms that exit before completing one year	1
total	38

iteratively for each technology level in the grid. Price indices are fixed points because they enter into firms' prices through material inputs. Given price indices, the demand function $\chi(\tau)$ in equation (14) is also iteratively calculated as a fixed point for each technology level in the grid. Demand is a fixed point because firms' demand for materials enter into $\chi(\tau)$ thereby affecting sales and demand for materials.[25] Given P and χ, we calculate the profit of each firm for each of its 801 discrete choices and update its optimal choice. The equilibrium is attained when no firm changes its choice. The parameter estimates minimize the squared distance between the moments from these generated data and the observed moments, weighted by the inverse of their variance.[26] Implicitly, this procedure takes labor supply $L(w)$ to equal firms' demand for labor and trade deficit D_H to equal the difference between estimated imports and exports.

Stage 1 moments The list of the 38 moments is on table 2. We match the 10%, 25%, 50%, 75%, 90% of the unconditional distribution of the log of normalized domestic sales—i.e.,

[25] In estimating P and χ, instead of aggregating over 5000 firms, we use the results in Melitz (2003) to aggregate over the representative firm in each of the 800 discrete choices. This significantly speeds up computation, since less than one-quarter of the possible choices are picked in a typical iteration.

[26] The variance of moments is calculated by randomly drawing the set of firms with replacement and recalculating the moments. To calculate moments on market shares, we multiply generated shares by 5000/7096 where 7096 is the number of plants in the data. Computational constraints impede us from simulating more firms, but in appendix E, we show that parameter estimates do not change much when the vectors of random variables change.

domestic sales divided by total manufacturing absorption in Colombia.[27] We classify firms according to their quartile of domestic sales, and for each quartile, we match: The percentage of firms importing and exporting, average share of foreign in material spending, average share of exports in firm sales. We classify firms into quartiles of domestic sales and quartiles of average wages, and match the percentage of firms in each combination of quartiles. That is, we match the percentage of firms in each of the sixteen bins in figure 4(a), where a firm's quartile of wage in the model equals its quartile of technology choice. In principle, we cannot observe the percentage of firms that never produce, but we take the percentage of plants that exit before the first year anniversary in Colombia to be the exiting firms in the model.[28]

Stage 1 identification While the formal estimation procedure is above, we informally discuss parameter identification here. The distribution of firm productivity $z(\omega, 0)$ captures primarily the distribution of market shares, whose overall level depends on import penetration. Since $p^* = 1$, parameter μ_1 governs import penetration by increasing the productivity in Home relative to Foreign, while parameter σ_1 governs the variance of market shares. Given the size of the Home market, approximately Y/α with $Y = 1$, parameter Y^* governs export intensity. By allowing some firms to be more productive in higher-technology goods, σ_2 governs the joint distribution of sales and wages.

Fixed trade costs $f_X(\omega)$ and $f_M(\omega)$ govern firms' import and export status and their correlation with sales. Fixed costs of production $f(\tau)$ has two parameters. Parameter f_1 is the production cost at $\tau = 0$ and governs firm exit. Parameter f_2 governs the distribution of technology choices and ensures that τ are spread in the range $[0, 10]$ used for computation.[29] Given

[27] This normalization of sales by absorption is standard, see Tybout (2003). Between 1988 and 1994 the Colombian economy grew, but since this growth is generally not associated with the trade liberalization, normalizing sales by absorption eliminates growth. We calculate absorption in the data as total sales in our manufacturing survey plus Colombian manufacturing imports minus exports from Feenstra et al (2005).

[28] This moment (8.7%) is taken from Eslava et al. (2004).

[29] The optimization algorithm penalizes parameter estimates that yield a mass of firms with corner solutions $\tau \in \{0, 1\}$ or a large clustering of technology choices. Small changes in f_2 and in the distribution of technology choices do not change the results. But large changes matter not just for computation. For example, if $f_2 = 0$ in the SI model, technology choices are still within $[0, 10]$ but the model predicts a weaker correlation between firm sales and wages than in the data. Or if the spread in technology choices is too large, then import and export intensity rise too fast with firm sales. In sum, f_2 is only weakly identified in the data, but for computational reasons, it is important for it to be free.

Table 3: Parameter estimates

	NSI model		SI model	
parameter	estimate	std. error	estimate	std. error
μ_1	-0.31	0.02	-0.11	0.02
σ_1	0.68	0.01	0.69	0.01
σ_2	2.8e-3	1.9e-4	3.6e-3	1.7e-3
f_1	2.3e-3	3.2e-4	1.4e-3	3.0e-4
f_2	4.4e-11	1.0e-11	1.4e-4	5.0e-5
μ_M	-3.6	0.12	-3.4	0.05
σ_M	1.4	0.09	1.5	0.06
μ_X	0.25	0.31	-0.17	0.09
σ_X	1.9	0.08	1.9	0.05
Y^*	0.54	0.01	0.19	0.03
T^*	3.8	0.46	3.7	0.06
τ^*	-	-	10.9	0.09

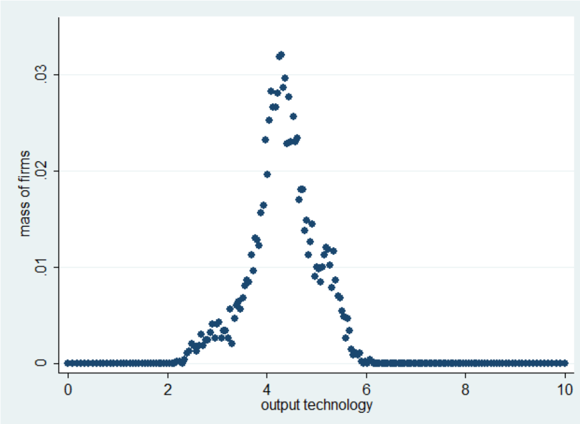
the technology distribution, the technology of Foreign imports τ^* governs the relation between import intensity and size, and T^* governs export intensity and size.

4.1.2 Stage 1: Results

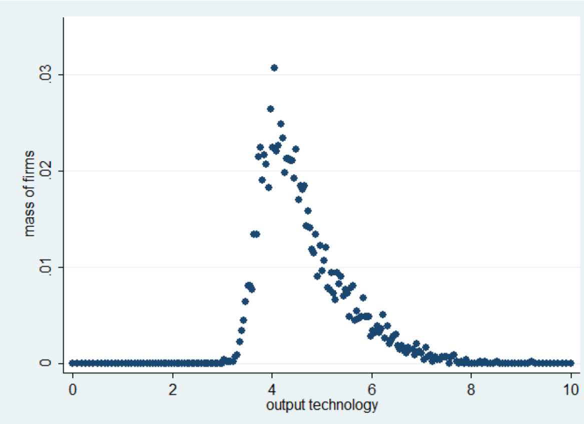
The cross-sectional predictions of the two models in stage 1 are strikingly similar. On table 3, the confidence intervals of almost all parameter estimates of the two models overlap.[30] In both models, fixed cost of production is small, the average fixed cost paid for importing is about \$50,000, and for exporting, it is \$130,000 in 2000 US dollars.[31] The distributions of technology choices are in figure 3. The relative demand for higher-technology goods is larger in Foreign than for the Home consumer—$T^* = 3.5$ in the NSI model and $T^* = 3.7$ in the SI model. In the SI model, Foreign goods are also of higher technology—$\tau^* = 10.9$ is higher than even the

[30]The exception is μ_1, which governs import penetration. The estimate is lower for the NSI model where τ^* is fixed to zero than for the SI model where $\tau^* = 10.9$. Although the SI model matches imports only slightly better than the NSI model, the added parameter in the SI model, τ^* is well identified. If τ^* is too small, then the model predicts that import intensity conditional on importing increases sharply with firm size. If τ^* is too large, the distribution of technology choices becomes too dispersed and bimodal—with importers choosing much higher technologies than other firms—thereby distorting the predictions on export behavior and on the joint distribution of sales and wages.

[31]These numbers are in line with Cherkashin et al. (2012) and Das et al. (2007). They are large because they reflect the expected profits from importing and exporting. We infer fixed costs in US\$ in the model through the estimated ratio of average sales to fixed costs assuming that average sales is the same as in the data, since average sales in the model are fixed through the normalization $Y = 1$.



(a) SI model



(b) NSI model

Figure 3: Distribution of technology choices

Table 4: Unconditional distribution of log(normalized domestic sales)

	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}
data	-12.5	-12.0	-11.1	-9.9	-8.4
SI model	-12.9	-11.9	-10.8	-9.5	-8.3
NSI model	-12.7	-11.8	-10.7	-9.5	-8.4

highest Home technology, $\tau = 6.11$.

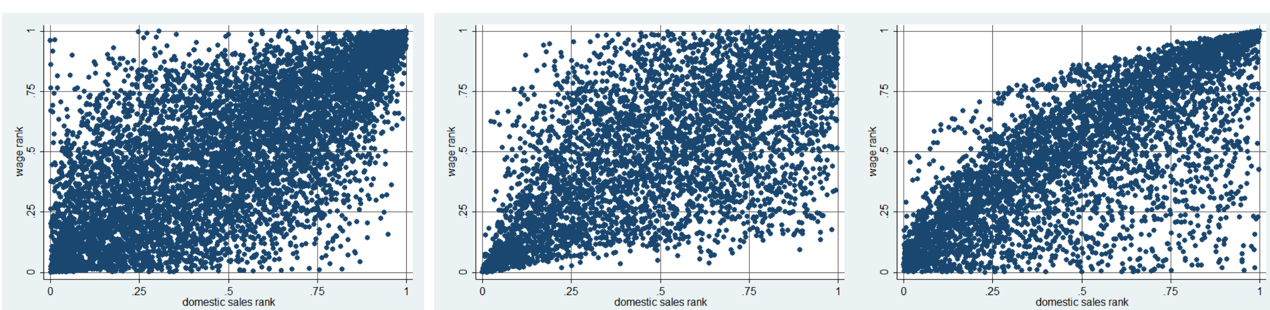
The two models match well the distributions on tables 4 and 5. Consistent with the data, firms in the upper quartiles of sales are generally more likely to import and export, they export a higher share of their output and import a higher share of their inputs. The model also replicates well the increasing relation between sales and wages in figure 4, though the NSI model has some difficulty in generating firms with high wages and low sales.[32] The large spread in this distribution suggests that economies of scale are not important determinants of technology choices. Exit upon entry is 8.7% in the data, 7.3% in the NSI model and 7.2% in the SI model.

Despite similarities, the two models differ in their underlying mechanism. Technology choices are constrained by the availability of high-tech inputs in the SI model, and by firm specific productivity $z_2(\omega)$ and fixed costs in the NSI model. Sections 4.2 and 4.3 below find support for the SI mechanism in cross-sectional data, while section 5 highlights its implications with a counterfactual trade liberalization.

[32]The model does better if we allow fixed production costs $f(\tau)$ to be firm-specific. But none of the other results, including the counterfactual below, change.

Table 5: Joint distributions of sales with other characteristics (in %)

	quartiles of domestic sales			
	1	2	3	4 (largest)
share of exporting plants				
data	3.1	4.3	8.7	30
SI model	2.5	6.6	12	28
NSI model	2.5	6.5	11	26
export sales/total sales				
data	1.8	1.2	1.6	5.5
SI model	0.4	1.2	2.1	5.4
NSI model	0.4	1.3	2.2	5.8
share of importing plants				
data	5.6	11	23	57
SI model	4.0	14	27	56
NSI model	2.1	9.1	23	57
spending on imported materials/total				
data	1.4	3.6	7.3	18
SI model	1.2	4.6	8.9	20
NSI model	0.5	2.3	6.0	15



(a) Data (b) SI model (c) NSI model

Figure 4: Distribution of firm domestic sales and wage

4.2 Stage 2: Skills

4.2.1 Stage 2: Estimation procedure

There are 4 parameters and 11 moments. We parameterize the model, describe the simulation, present the moments and discuss the identification of parameters. Results are in section 4.2.2.

Stage 2 parametrization We set $w_u = 1$ and estimate the skill premium w_s/w_u. The elasticity of substitution σ_L is not separately identified from Φ_L. We set $\sigma_L = 1.6$ from Acemoglu and Autor (2010) and experiment with other values in appendix **??**. The demand for skilled relative to unskilled labor in equation (10),

$$\frac{l_s}{l_u} = \left(\frac{w_s}{w_u}\right)^{-\sigma_L} \frac{\Phi_L(s,\tau)}{\Phi_L(u,\tau)},$$

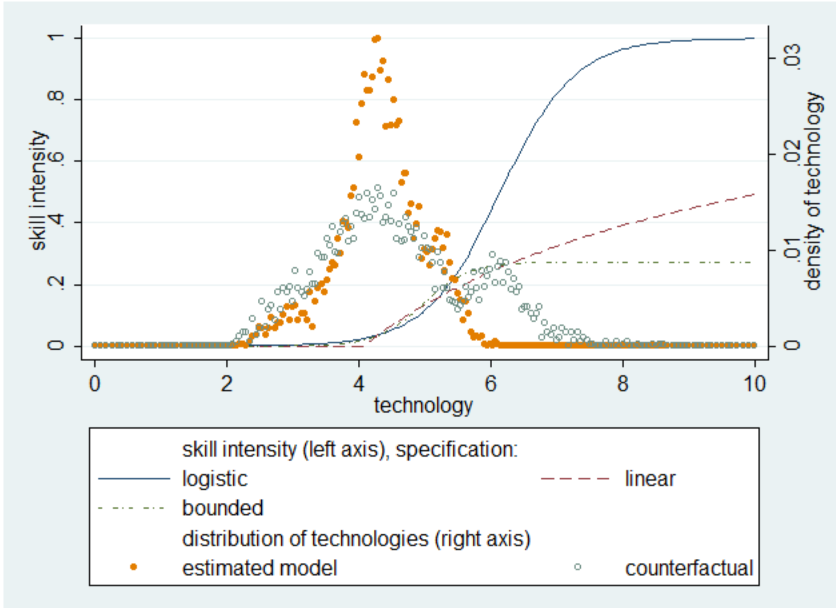
depends on the ratio $\frac{\Phi_L(s,\tau)}{\Phi_L(u,\tau)}$ and not on the level of productivity shifters Φ_L which can be factored out into productivity parameters $z(\tau,\omega)$. So, we parameterize $\frac{\Phi_L(s,\tau)}{\Phi_L(u,\tau)}$ and choose $\Phi_L(u,\tau)$ judiciously for each parameter guess so that $w(\tau) = 1$ for all τ.[33] This parametrization is critical because $\frac{\Phi_L(s,\tau)}{\Phi_L(u,\tau)}$ governs the relative demand for skilled workers in the estimated and in the counterfactual technology choices. While the first is well identified with 1988 data, the later cannot be. To make this point clear, consider three specifications:

$$\begin{aligned}
\frac{\Phi_L(s,\tau)}{\Phi_L(u,\tau)} &= \exp(l_1 + l_2\tau) && \text{logistic}\\
\frac{\Phi_L(s,\tau)}{\Phi_L(u,\tau)} &= \max\{0, l_1 + l_2\tau\} && \text{linear}\\
\frac{\Phi_L(s,\tau)}{\Phi_L(s,\tau)+\Phi_L(u,\tau)} &= l_3\frac{\exp(l_1 + l_2\tau)}{1+\exp(l_1 + l_2\tau)} && \text{bounded}
\end{aligned}$$

where l_1, l_2 and $l_3 \in [0,1]$ are parameters to be estimated. Figure 5 illustrates the results. On the left y-axis is skill intensity as a function of technology choices in the model estimated using the three specifications above. On the right y-axis is the distribution of technology choices from stage 1 (solid circles) and from the counterfactual trade liberalization of section 5 below (hollow

[33] That is, $\Phi_L(u,\tau) = \left[1 + \frac{\Phi_L(s,\tau)}{\Phi_L(u,\tau)}\left(\frac{w_s}{w_u}\right)^{1-\sigma_L}\right]^{-1}$.

Figure 5: Comparison between three specifications for $\frac{\Phi_L(s,\tau)}{\Phi_L(u,\tau)}$



circles). We take the counterfactual where labor is perfectly elastic, and hence counterfactual technologies do not depend on the estimates of Φ_L, and skill intensity for a given τ is the same before and after the counterfactual.

The three specifications make similar predictions for the estimated model $\tau \leq 6$, but wildly different counterfactual predictions. For example, the 95$^{\text{th}}$ percentile of the technology distribution is $\tau = 5.4$ in the estimated model and $\tau = 6.5$ in the counterfactual. When $\tau = 5.4$, skill intensity is around 20% in all three specifications, but when $\tau = 6.5$ the skill intensity is 27% in the bounded specification, 28% in the linear specification and *63% in the logistic specification.* Throughout our analysis, we use the bounded specification because it makes more conservative (and arguably realistic) counterfactual predictions. In this specification, skill intensity has an upper bound, captured by l_3, as technology goes to infinity. We use data on the skill premium and manufacturing skill intensity in the United States from Autor, Katz and Krueger (1998) to pick parameter l_3.[34]

Finally, the data report the share of white- and blue-collar workers, not their skill. Firm

[34] We assume that foreign technology $\tau^* = 10.9$ corresponds to USA technology. We then calculate the model's predicted skill intensity if firms were faced with the skill premium in the USA, $\frac{w_s}{w_u} = 1.73$ (= exp(0.549) in the 1990 Census, table 1, page 1174), and match it to the manufacturing skill intensity in the USA, 39.3% (college equivalents in the 1990 Census, Appendix 1, page 1209).

characteristics such as sales, importing and exporting are much more correlated with wages than with the share of white-collar workers. Our interpretation is that firms observe skill better than we econometricians and that wages reflect the true ranking of skill intensity across firms better than the share of white-collars. Accordingly, we assume measurement error in skills. A share $\pi_u(\omega)$ of firm ω's unskilled workers are misclassified as white-collars, where $\pi_u(\omega)$ is independently drawn from a logistic distribution truncated in [0,1] with mean parameter zero and variance parameter σ_π. All skilled workers are white-collars.[35]

Stage 2 simulation For each firm, we fix its technology τ from stage one and take a random draw from a uniform distribution. Given a guess of parameters, we calculate firms' skill intensity and average wage, and transform the random draws to get the share of white-collar workers.

Stage 2 moments There are 11 moments: **(5)** The 10%, 25%, 50%, 75%, 90% of the distribution of the share of white-collar workers, **(4)** the average share of white-collar workers by quartile of domestic sales, **(1)** the total share of white-collar workers in manufacturing, and **(1)** the average wage of white-collar workers divided by average wage of blue-collar workers.

Stage 2 identification While the first stage delivers the joint distribution of ranking of unobserved skill intensity and sales (figure 4(b)), here we target the joint distribution of sales with white-collar shares. To the extent that the later relationship is weaker than the former, the model predicts larger measurement error σ_π. Given these errors and technology choices from the first stage, the ratio $\frac{\Phi_L(s,\tau)}{\Phi_L(u,\tau)}$ governs the unconditional distribution of skill intensity and the skill premium governs the measured skill premium.

4.2.2 Stage 2: Results

The parameter estimates are on table 6. Again the NSI and the SI models deliver similar parameter estimates and fit. The models fit well the targeted moments on table 7, on the

[35] We assume that skilled workers are not misclassified for several reasons. First, in the data, the wages of white-collars vary a lot more than that of blue-collars across firms, suggesting that the presence of college graduates among blue-collars is not common. Second, if classification errors also applied to skilled workers, their share in manufacturing would be close to the white-collar share, which is about 50%, much higher than the share of college graduates in Colombia.

Table 6: Parameter estimates of stage 2, SI model

	SI model		NSI model	
parameter	estimate	std. error	estimate	std. error
w_s/w_u	2.43	0.21	2.42	0.18
σ_π	0.18	0.01	0.18	0.01
l_1	-4.8	0.06	-5.6	0.13
l_2	2.9	0.60	1.26	0.26
l_3	0.61	-	0.61	-

Table 7: Distribution of skill intensity (in %)

unconditional	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}
data	7.7	14	24	38	56
SI model	7.5	14	25	38	55
NSI model	7.7	14	24	38	55
by quartile of domestic sales					
	1	2	3	4 (largest)	
data	23	25	29	36	
SI model	24	26	31	33	
NSI model	25	26	30	33	

distribution of skill intensity unconditional and conditional on domestic sales. Table 8 shows aggregate skill premium and skill intensity. Targeted moments on white- and blue-collar workers are similar in the data and in the model. And the model's predictions on nontarget, unobservable skill are very well aligned with Attanasio et al. (2004) who use Colombian household survey data. They document that about 10% of heads of households in Colombia had a college degree during the trade liberalization, and that the skill premium in 1988 was $w_s/w_u = 2.6$ for university to elementary school and 1.9 for university to secondary school. Our estimated skill intensity is 15% and skill premium is 2.4 in the SI and NSI models.[36]

The SI model predicts that high-tech, skill intensive firms are more likely to import and they import a higher share of their inputs after controlling for sales. Both of these predictions are bore out by the data on table 9, though the model overestimates first and underestimates the second. After controlling for sales, a 10% increase in skill intensity increases the probability of importing by about 3.3% in the model and by 0.4% in the data. And on table 9, a 10 percentage

[36]Our estimates are even more plausible if one considers that manufacturing in developing countries is generally more skill intensive than services and agriculture. See Young (2013).

Table 8: Aggregate skill intensity and premium

measured skill (targeted)	data	SI model	NSI model
skill intensity L_{white}/L	0.31	0.34	0.35
skill premium $w_{\text{white}}/w_{\text{blue}}$	1.62	1.62	1.62
unobserved skill (out of sample)	Colombian avg.†	SI model	NSI model
skill intensity L_s/L	0.10	0.15	0.15
skill premium w_s/w_u	1.9 - 2.6	2.4	2.4

†The Colombian average is from Attanasio et al. (2004).

Table 9: Predicted and observed import patterns

A. Dependent variable: Import dummy			
	data	SI model	NSI model
white-collar shares	0.044**	0.32***	0.003
	(0.022)	(0.03)	(0.028)
number of observations	7015	4639	4633
B. Dependent variable: Import intensity (importers only)			
	data	SI model	NSI model
white-collar shares	0.12***	0.06***	0
	(0.03)	(0.01)	-
number of observations	1714	1165	1055

Panel A shows the coefficient on an import dummy from an OLS regression of the white-collar shares on an importer dummy and on log of firm sales. Panel B shows the coefficient on the white-collar shares from an OLS regression of import intensity (spending on foreign materials/total spending on materials) on white-collar shares and log of sales. Data regressions include sector fixed effects. Standard errors are in parenthesis. ** indicates statistical significance at 95% level, and *** statistical significance at 99% level.

point increase in an importing firm's white-collar share is associated with an increase in import intensity by 1.2 percentage points in the data and 0.6 points in the model. In the NSI model, all firms value inputs equally, and hence there is no systematic variation in importing patterns after controlling for total sales.

4.3 Stage 3: Unit prices

4.3.1 Stage 3: Calibration procedure

Technology upgrading in the model may take several forms—e.g., quality improvements, investing in the brand or in the reliability of products—many of which affect unit prices. As the model stands, productivity shifters $\Phi(\tau, \tau')$ captures how the valuation of an input of type τ varies across firms of different output types τ'. To match prices, we augment the model to capture the valuation of a good of type τ that is common to all firms (and consumers). Re-define input productivity shifter $\Phi(\tau, \tau')$ in equation (11) and firm-specific productivity parameters $z(\tau, \omega)$ in equation (20), respectively, as

$$\Phi(\tau', \tau) = \overline{\Phi}(\tau) \left[\frac{\exp(\tau' - \tau)}{1 + \exp(\tau' - \tau)} \right]$$
$$z(\tau, \omega) = \overline{z}(\tau) \left[\max\{0, z_1(\omega) + z_2(\omega)\tau\} \right].$$

The terms in square brackets are the original equations to which we have added multipliers $\overline{\Phi}(\tau)$ and $\overline{z}(\tau)$. Function $\overline{\Phi}(\tau)$ is a productivity shifter associated with *inputs* of type τ agreed upon by all buyers, and function $\overline{z}(\tau)$ is a productivity shifter associated with *output* of type τ that is common to all producing firms. If $[\overline{z}(\tau)]^{\sigma-1}\overline{\Phi}(\tau) = 1$ for all τ, then the firm's problem in equation (15) does not change and hence our estimates from stages 1 and 2 do not change. The idea is that as output technology τ increases, the marginal productivity $\overline{z}(\tau)$ may decrease, but the ensuing increase in price is offset by a higher demand for goods of type τ captured by function $\overline{\Phi}(\tau)$. Firm ω sets price $p = \mu \frac{C(\tau, 1_M(\omega))}{z(\tau, \omega)}$ where the markup, aggregate input costs C, the firm's technology choice τ and productivity draws $z_1(\omega)$ and $z_2(\omega)$ are all taken from stage 1. We parameterize $\overline{z}(\tau) = \exp(\tilde{z}\tau)$ and estimate $\tilde{z}$ to exactly match the coefficient from regressing the log of unit prices of firms' output on the log of firms' total sales. We focus exclusively on the SI model where input prices vary with firm characteristics.

Table 10: Input and output prices

A. Dependent variable: log of output unit prices				
	data		model	
ln(total sales), **targeted**	0.0118		0.0118	
	(0.006)		(0.004)	
white-collar shares		0.364		0.478
		(0.058)		(0.037)
number of observations	20,786	20,786	4639	4639
B. Dependent variable: log of input unit prices				
	data		model	
ln(total sales)	0.0136		0.0076	
	(0.003)		(0.0001)	
white-collar shares		0.269		0.028
		(0.029)		(0.001)
number of observations	71,648	71,648	4639	4639

Standard errors are in parenthesis. All coefficients are statistically significant at a 99% level. Data regressions contain dummies for the product and for the sector of the firm.

4.3.2 Stage 3: Results

The calibrated $\tilde{z} = -1.01 < 0$ indicating that variable costs generally increase with technology. Table 10 displays patterns on unit prices. In panel A, the unit price of firms' outputs increases more with white-collar shares than with sales in the data and in the model. Firms with higher sales and shares of white-collar workers both sell at higher unit prices because they produce higher technology, but this effect is partially offset by a higher productivity parameter z among larger firms. Material prices are less correlated with firm characteristics than output prices because firms tend to source from a variety of inputs, not all corresponding exactly to its output type. The model matches well the relation between input prices and sales reasonably well and underestimates the relation between unit prices and white-collar shares.

To summarize, technology choices in the model provide a unified explanation for well-documented cross-sectional correlations between sales, wages, skill intensity, prices, import and export participation and intensity. Our estimation shows that the model can also quantitatively match the joint distribution of firm characteristics. The SI and NSI models capture equally well within-sample moments, but the SI model captures reasonably well out-of-sample moments, on importing behavior and input prices, that lend support to the SI assumption that higher-type goods take in higher-type inputs. Next we show that this SI assumption greatly magnifies the effect on international trade on technology and demand for skilled workers.

5 Pre- versus post-trade liberalization

5.1 Counterfactual procedure

The procedure to simulate the trade liberalization is here and the results are in sections 5.2 and 5.3. We exogenously decrease tariffs to match the Colombian manufacturing average of 27.7% in 1988 and 11.8% in 1994. Although the trade liberalization is unilateral, exports may expand for various reasons. For example, the Colombian peso may depreciate, or imported inputs may decrease the price and increase the technology of domestic goods, making them more competitive abroad.

The model, however, cannot predict changes in imports and exports without additional information on non-tariff barriers, trade deficit, etc. So, we allow Foreign prices p^* and market-size parameter Y^* to change to exactly match the aggregate change in imports and exports. To be specific, between 1988 and 1994, manufacturing imports expanded from 13.8% to 28.1% of manufacturing absorption in Colombia, and exports expanded from 6.1% to 7.5%. We match this 14.2% points expansion of imports and 1.5% points expansion of exports. So, *the counterfactual studies the model's changes in technology and in demand for skills given observed changes in trade flows.* Changes in Y^* reflect movements in real exchange rates or any other factor influencing growth in world manufacturing absorption relative to Colombia's, and changes in p^*/Y^* reflect non-tariff barriers.

The cross-sectional data contain no information on the elasticity of labor supply, only on the supply of skilled and unskilled labor given pre-liberalization wages. To clearly understand the workings of the model, we make the two extreme assumptions: Labor is perfectly elastic and wages (w_u, w_s) do not change in section 5.2, and labor is perfectly inelastic and labor supply (L_u, L_s) does not change in section 5.3. In the data, the skill premium and skill intensity in manufacturing increased in Colombia between 1988 and 1994, suggesting that labor in and out of manufacturing is imperfectly elastic.

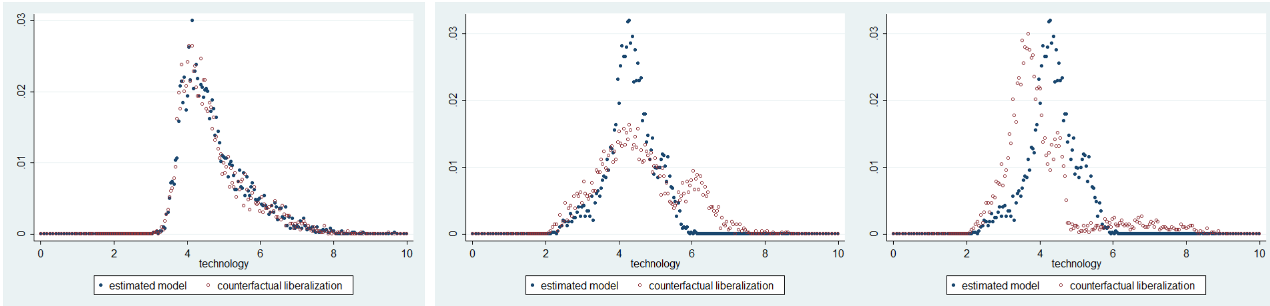
5.2 Counterfactual results: Elastic labor

Figure 6 shows the distributions of technology choices in the NSI and the SI model. The changes do not depend on the second stage parametrization of skill intensity because, when labor is perfectly elastic, the CES cost of labor $w(\tau)$ does not change. Technologies practically do not change in the NSI model and change significantly in the SI model, especially in the upper tail of the distribution. To get a sense of magnitude, using post-liberalization price indices, the movement in technology of a typical large firm from $\tau = 5.4$ to $\tau = 6.5$ is associated with an increase in import intensity from 45% to 57%.[37]

In the NSI model, firms upgrade technology if their economies of scale increase or if foreign sales increase relative to domestic sales, because Foreign has a higher relative demand for high-tech goods. Both effects are small. Recall that exports increase by only 1.5% of domestic absorption and imports increase by 14%. So, the Foreign share in sales does not change much and sales decrease by 17 log-points on average. But economies of scale play a minor role in technology choices, as suggested by the cross-sectional results in section 4.1.2. Firm exit also plays a minor role—the 3% of firms that exit are too small to contribute to aggregate changes.

Additional mechanisms for technology upgrading in the SI model are: The decrease in the price of high-tech Foreign inputs disproportionately decreases the cost of producing higher-tech goods. As domestic production shifts toward high-tech firms and domestic firms upgrade their technology, the relative cost of high-tech domestic inputs fall and the relative demand for them rises. Changes in the prices of Home and Foreign inputs are large. The aggregate cost of material inputs $P(\tau, 1_M)$ for producing a good of high-type $\tau = 6$ relative to a low-type $\tau = 2$ decreases by 9% for importing firms and by 13% for non-importers. The drop is larger for non-importers because high-type inputs are previously not available in the domestic market, but both sets

[37]Technologies $\tau = 5.4$ and $\tau = 6.5$ are, respectively, the 95$^{\text{th}}$ percentile of the pre- and post-liberalization distribution. The change in import intensity is even larger, from 37% to 55%, if we use pre-liberalization prices because domestic inputs have lower technologies before the counterfactual.



(a) NSI model, elastic labor (b) SI model, elastic labor (c) SI model, inelastic labor

Figure 6: Distribution of technology choices

of firms benefits from changes in the domestic input market.[38] Changes in domestic demand function χ, in turn, are smaller. Because *ex ante* low-tech firms downgrade their technology and high-tech firms upgrade, the demand for medium-type goods, $\tau = 6.0$, decreases by about 3% relative to low- and high-type goods.

Table 11 summarizes the results for a partition of firms according to their participation in international trade. The SI and the NSI model have similar predictions regarding sales and the classification of firms by their participation in international trade. But in the NSI model, only 6% of firms upgrade technology, and all non-exporting firms downgrade—as in the basic model of section 1. In contrast, 57% of firms upgrade in the SI model. Among firms that never engage in international trade, 37% upgrade their technologies despite a 23% drop in sales. The corresponding changes in skill intensity, on table 12, are also large. On average, skill intensity increases from 15% to 22% in the SI model. New importers and exporters experience the largest changes and domestically-oriented firms increase their skill intensity from 4% to 6%.[39]

Table 13 compares the counterfactual results to 1994 post-liberalization data. In the two models and in the data, sales generally decrease, especially among smaller firms. White-collar shares do not change much in the NSI model, while in the data and in the SI model, white-collar shares increase and they increase especially in the upper tail of the distribution. The predictions of the SI model are not far from the data, but the model overestimates decreases in sales and

[38]There is no neat decomposition of material prices $P(\tau, 1)$ between Home and Foreign inputs. The relative cost of high- and low-tech materials decreases by 6.0% if we only change Home prices and by 5.6% if we only change Foreign prices.

[39]Evidence for technology upgrading among new exporters appears in Bustos (2011) and Lileeva and Trefler (2010).

Table 11: Summary of counterfactual by participation in international trade

	domestic oriented	continuing importers	continuing exporters**	new importers†	new exporters**	all firms
NSI model						
share of firms	67%	18%	11%	3.7%	0.3%	100%
log change in sales	-0.27	-0.21	-0.14	-0.09	0.14	-0.17
share of firms upgrading	0	0	47%	18%	100%	6.1%
SI model, elastic labor						
share of firms	65%	19%	12%	3.1%	0.5%	100%
log change in sales	-0.26	-0.20	-0.14	-0.07	0.08	-0.17
share of firms upgrading	37%	94%	100%	99%	100%	57%
SI model, inelastic labor						
share of firms	66%	19%	12%	2.7%	0.2%	100%
log change in sales	-0.25	-0.19	-0.14	-0.06	0.09	-0.17
share of firms upgrading	0	16%	48%	88%	100%	11%

† includes firms that initially export only and start importing with the counterfactual.

** includes firms that import and export.

Table 12: Counterfactual changes in skill intensity (in %)

	domestic oriented	continuing importers	continuing exporters**	new importers†	new exporters**	all firms
NSI model						
initial skill intensity	8.0	13	21	14	20	15.3
counterfactual	7.4	12	21	14	23	15.5
Δ = counterfactual-initial	-0.7	-0.6	0.4	0.3	2.8	0.2
SI model, elastic labor						
initial skill intensity	4.1	15	19	5.9	14	14.6
counterfactual	6.1	24	25	25	26	21.7
Δ = counterfactual-initial	2.1	8.7	5.9	18.7	11.4	7.1
SI model, inelastic labor						
initial skill intensity	4.2	15	19	5.9	15	15
counterfactual skill intensity	1.0	9.7	22	12	25	15
Δ = counterfactual-initial	-3.2	-5.5	2.6	6.1	9.4	0

† includes firms that initially export only and start importing with the counterfactual.

** includes firms that import and export.

Reported skill intensity is aggregate. For example, 15% of all employees are initially skilled.

Table 13: Changes in the distributions of sales and skill intensity

	percentiles					
	10%	25%	50%	75%	90%	**total†**
ln(normalized sales), $\Delta = 1994 - 1988^*$						
data	-0.16	-0.10	-0.06	0.04	-0.08	**-0.13**
NSI model	-0.27	-0.27	-0.25	-0.23	-0.18	**-0.18**
SI model, elastic labor	-0.26	-0.26	-0.24	-0.22	-0.20	**-0.17**
SI model, inelastic labor	-0.24	-0.23	-0.23	-0.21	-0.19	**-0.17**
white-collar shares, $\Delta = 1994 - 1988$ **in %**						
data	1.4	2.4	3.9	5.4	8.1	**4.6**
NSI model	-0.20	-0.24	-0.20	-0.21	-0.22	**0.03**
SI model, elastic labor	0.4	1.8	4.1	3.7	3.0	**5.6**
SI model, inelastic labor	-2.4	-3.0	-2.1	-1.3	-0.7	**0**

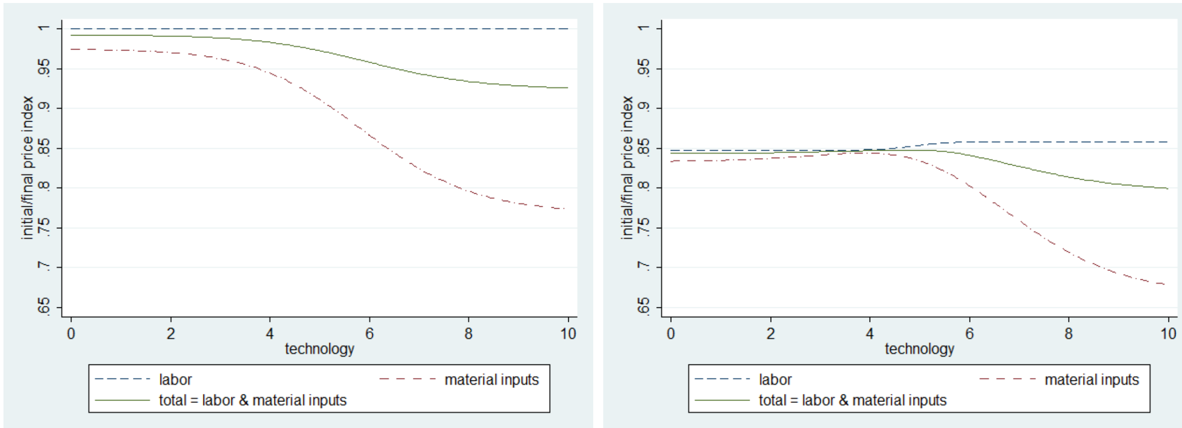
*A firm's normalized sales are its total sales divided by the sales of domestic and foreign firms in Home. † Changes in total skill intensity are larger than shifts in percentiles because labor shifts from less to more skill-intensive firms. See appendix C.

underestimates increases in skill intensity if one considers that the skill premium in the data increases by 11% between 1988 and 1994.

5.3 Counterfactual results: Inelastic labor

We focus exclusively on the SI model because the elasticity of labor supply is irrelevant in the NSI model where the relative demand for skilled labor did not change with the counterfactual. The results are presented in parallel to the elastic labor case above for easier comparison. The skill premium w_s/w_u increases by 2.7%, from 2.4 to 2.5, confirming that trade increases the demand for skills in the model but by less than in the data.

The counterfactual distribution of technology choices appears in figure 6. To understand the difference from the elastic-labor case, figure 7 decomposes total changes in input costs for a non-importing firm $C(\tau, 0) = w(\tau)^{\alpha} P(\tau)^{1-\alpha}$ into labor costs $w(\tau)$, material input costs $P(\tau)$. When labor is elastic, there is no change in wages and relative costs of materials decrease monotonically with technology τ, thereby pushing all firms toward technology upgrading. In the inelastic-labor case, the cost of labor decreases by about 15% to maintain the demand for labor (L_s, L_u) constant at the same time that sales decrease by about 15% (-0.17 log points). In addition, a 2.7% increase in the skill premium leads to a 1% increase in labor costs $w(\tau)$ for high-



(a) Elastic labor

(b) Inelastic labor

Figure 7: Counterfactual changes in input costs by technology τ

relative to low tech goods.[40] Albeit small, this change, together with the fall in sales, leads some medium- and low-tech firms to downgrade their technologies. As they do so, the availability of medium-tech inputs decreases in the domestic market leading even more firms to downgrade. The relative cost of producing medium-type goods consequently increases relative to low- and to high-type, thus explaining the hump-shaped pattern of cost changes in figure 7(b). So, for low-tech firms, the effect of the domestic input market on technology choices is negative, but for high-tech firms, it is large, positive and similar to the elastic-labor case. Taking the pre- and post-liberalization 95$^{\text{th}}$ percentile of the technology distribution, the relative material input cost $\frac{P(6.4)}{P(5.4)}$ decreased by 5.5% when labor is elastic and 5.4% when labor is inelastic.

It is almost by construction that small firms downgrade their technologies when labor is inelastic. Because the elasticity of substitution between skilled and unskilled labor is small, $\sigma_L = 1.6$, changes in the skill premium do not lead to changes skill intensity for a given τ—firms increase their skill intensity if and only if they upgrade their technology. Moreover, importers and exporters are large. So, a small increase in these firms' demand for skilled workers has to be offset by large and widespread decreases in the demand for skilled workers among smaller, technologically backward firms. What is perhaps surprising is that a 2.7% increase in the skill premium suffices for labor markets to clear. The same linkages that led to large and ubiquitous

[40]The scale of figures 7(a) and 7(b) are different because in the inelastic-labor case the wages of skilled and unskilled workers decrease by about 15% in order for labor markets to clear despite the fall in firm sales.

technology upgrading when labor was elastic now leads low-type firms to downgrade. For large firms, these linkages continue to have a large, positive effect on technology. And relative to the NSI model where there is no increase in demand for skilled labor, the SI assumption that higher-technology firms use higher-technology inputs increases the skill premium significantly, though not dramatically, by 2.7%.

6 Scale, exports, and capital goods

The benchmark counterfactuals above under predict the effects of trade in the demand for skilled workers, suggesting not surprisingly that other forces are at work. This section considers three alternative counterfactuals that improve our understanding of the model, and at the same time, point to other explanations: Free entry, an anticipation of export growth, and capital inputs.[41] We focus on the SI model with perfectly elastic labor supply, and cite the NSI and inelastic-labor cases only when the comparison is relevant. Table 14 summarizes the results.

Specifications A1 and A2 are better seen in conjunction. Specification A1 introduces free entry, but maintains the assumption that exports grow by 1.5% of absorption and imports grow by 14.2% of absorption to reflect changes in Colombia between 1988 and 1994. Recognizing that this asymmetric response is not sustainable in the long run, specification A2 assumes that exports also grow by 14.2% of absorption, and studies the effects of trade if firms invest in technology in anticipation of an eventual export expansion.[42] Because average sales do not change by assumption and fixed production costs are relatively small, introducing free entry to specification A2 would not change its results. In other words, sales increase relative to the benchmark in both A1 and A2, but the added sales go to Home in A1 and to Foreign in A2.

And because Foreign has a higher relative demand for high-tech goods, A2 predicts much larger technological upgrading, as per figure 8. Technology changes in A1 are very similar to the benchmark confirming that economies of scale have only a minor effect on technology choices.

[41] An additional explanation is a tendency in the data for the skill premium and skill intensity to rise over time in Colombia, like in the United States and other countries. But estimating the long-run trend, absent other changes, is difficult.

[42] Exports surged in 1999 after a large devaluation of Colombian pesos. Other countries that unilaterally liberalized to trade also experienced an initial larger increase in imports than in exports.

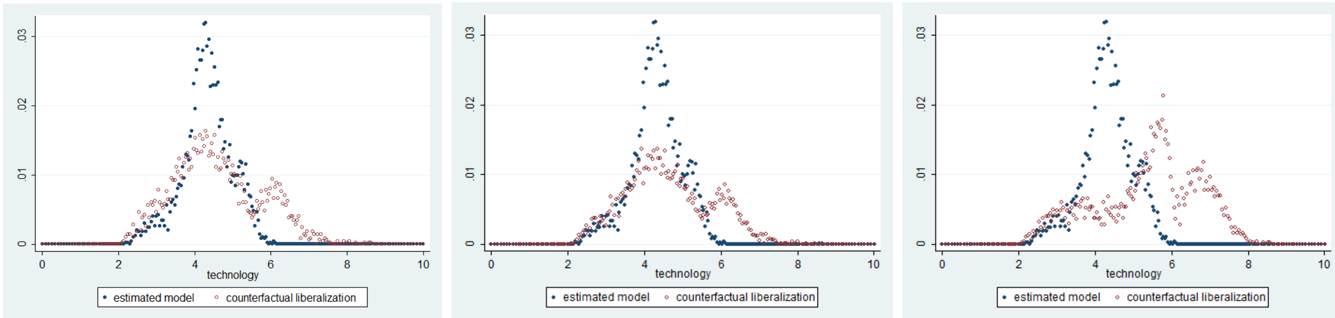
On table 14, new importers and new exporters experience the largest changes in all cases, but in A2 new exporters account for 5% of firms, compared to 0.5% in the benchmark. As a result, they catalyze much larger changes in the domestic input market. Even among domestically-oriented firms, 73% upgrade their technology and their skill intensity increases from 4% to 19%—a 15% point difference, compared with 2% points in the benchmark. In the NSI model (not shown), the export expansion in specification A2 also leads to upgrading among exporters, but these changes do not reverberate to the domestic market. Non-exporters continue to downgrade, aggregate skill intensity increases from 15% to 18%, by 2.5% points, and only 16% of firms upgrade. In the SI model, these numbers are much larger, 11% and 83%, respectively.

In specification A3, we interpret non-labor inputs more broadly to include capital equipment, not just materials, and we decrease the labor share in production from $\alpha = 0.7$ in the benchmark to 0.5.[43] Relative to the benchmark, a higher share of material inputs in A3 magnifies the effect of input linkages on technologies choices. The share of domestically-oriented firms that upgrade their technologies with trade increases from 37% in the benchmark to 71%. Aggregate skill intensity increases from 15% to 23%, by 8.4% points compared to 7.1% in the benchmark.

Consistent with the literature on capital-skill complementarities, international trade affects the demand for skilled workers in the model through investment in skill-bias technologies, which in the data may take the form of computers and other R&D intensive capital equipment.[44] Under the additional assumption that higher-τ goods contain a disproportionate amount of capital equipment, larger, more skill intensive and technologically advanced firms are more capital intensive in the cross-section, and Colombia is a net importer of capital equipment since Foreign goods are estimated to have higher-technology than Home's. While in previous papers, firms incentives to invest in more advanced technologies depend on the price of capital or on their direct engagement in international trade, here the costs and benefits of such investment depends on the extent to which other firms in the market also invest. Specification A3 suggests that this new channel is particularly large when inputs include capital equipment. Explicitly incorporating capital into the model and using data on different types of investment, potentially

[43] Parameter estimates are in appendix **??** and the cross-sectional moments practically do not change.

[44] See Autor, Katz and Krueger (1998), Berman, Bound, Griliches (1994) for the complementarity of skilled labor, computers and high-tech equipment. See Acemoglu (2002) for a survey on theories.



(a) Benchmark (b) A1: free entry (c) A2: export growth

Figure 8: Counterfactual changes in the distribution of technology

integrating our approach to Burstein, Cravino and Vogel (2013), is thus a promising path for future work.

The results above are obtained under the assumption of perfectly-elastic labor supply, but when labor is perfectly inelastic, counterfactual changes in the skill premium on table 15 convey the same messages. The NSI model predicts much smaller changes than the SI model. It predicts that the rise in the skill premium is 2.5% when exports expand (A2) and less than 1% in all other cases. The SI model predictions are again particularly large in cases of export growth (A2) and higher share of non-labor inputs (A3), where the rise in skill premium is 8.2% and 4.6%, respectively. Although these numbers are large, Attanasio, Goldberg and Pavcnik (2004) estimate that the skill premium in Colombia rose by 11% between 1988 and 1994.

The literature points to additional explanations. First, there is an upward trend in the skill premium in Colombia and elsewhere, possibly due to skill-bias technical change in the USA. This trend is not extracted from the 11% increase in the skill premium above. Second, lack of competition prior to the liberalization may have given rise to x-inefficiencies or agency problems within firms that depressed the skill premium and prevented the adoption of new technologies.[45] Third, in the model, the benefits of adopting higher-technology when other firms adopt increase in our model only through intermediate inputs, but there are other sources of of transmission such as learning from early adopters, the development of skills, etc.[46] While investigating these

[45]See Acemoglu (2003) for a survey on skill-bias technical change, Holmes and Schmitz (2010) for a survey on competition and efficiency, and Caliendo and Rossi-Hansberg (2012) for agency problems within firms. See also Thoenig and Verdier (2003) for an additional explanation.

[46]See Jovanovic (1982) on learning and Nabseth and Ray (1974) for micro-level studies on technology

Table 14: Summary of counterfactual by participation in international trade

	no trade	continuing importers	continuing exporters**	new importers†	new exporters**	all firms
benchmark: SI model with elastic labor supply						
share of firms (%)	65	19	12	3.1	0.5	100
log change in sales	-0.26	-0.20	-0.14	-0.07	0.08	-0.17
share of firms upgrading (%)	37	94	100	99	100	57
change in skill int.* (%)	2.1	8.7	5.9	19	11	7.1
A1: Free entry						
share of firms (%)	63	19	12	5.0	1.4	100
log change in sales	-0.08	-0.01	0.04	0.11	0.26	0.02
share of firms upgrading (%)	40	95	100	100	100	61
change in skill int.* (%)	2.1	8.5	5.8	18	13	7.3
A2: Export growth						
share of firms (%)	61	18	12	3.8	5.3	100
log change in sales	-0.27	-0.20	0.09	0.01	0.31	0.01
share of firms upgrading (%)	73	97	100	99	100	83
change in skill int.* (%)	15	11	6.3	20	13	11
A3: $\alpha = 0.5$						
share of firms (%)	70	15	11	3.0	0.2	100
log change in sales	-0.30	-0.19	-0.13	-0.01	0.09	-0.18
share of firms upgrading (%)	71	100	100	100	100	79
change in skill int.* (%)	4.0	11	6.3	20	13	8.4

† includes firms that initially export only and start importing with the counterfactual.

** includes firms that import and export.

* Changes in skill intensity is the counterfactual minus the initial level.

Table 15: Change in the skill premium $\frac{w_s}{w_u}$ when labor is inelastic (in %)

	Data*	Benchmark	A1: Free entry	A2: Export growth	A3: $\alpha = 0.5$
SI model	**11**	2.7	2.7	8.2	4.6
NSI model	**11**	0.16	0.50	2.5	0.26

* Estimated change in the skill premium in Colombia between 1988 and 1994 are from Attanasio, Goldberg and Pavcnik (2004).

explanations is beyond the scope of our paper, our central point still remains: As long as they lead to larger and more widespread improvements in technology, they are augmented through firms' interactions in the domestic input market.

7 Conclusion

The proposed model exhibits external economies of scale in the form of specialized inputs. Unlike previous models, however, production costs do not depend on the overall market size, but on the market for technologically advanced goods.[47] In sharp contrast to the infant-industry argument where trade barriers act as coordination devices in setting off the development of an industry, here, it is the removal of trade barriers that acts as a coordination device: The direct effects of trade on a minority of plants percolate through the domestic market, changing relative costs and demand and leading to large and widespread investments in technology. Firms with *ex ante* high-technology upgrade their technologies further, while *ex ante* low-tech firms downgrade—a heterogeneous effect consistent with previous empirical findings.[48] We apply the model to the Colombian trade liberalization, because the decrease in sales, widespread adoption of advanced technologies and increased demand for skilled workers that followed unilateral trade liberalizations in developing countries are puzzling. But we hope the model will find its way to other applications within and beyond the field of international trade.

adoption.

[47] See Rodriguez-Clare (2007), Melitz (2005) and references there cited. External economies of scale magnify the gains from trade in Lyn and Rodriguez-Clare (2014) and gains from trade are assured in Helpman and Rossi-Hansberg (2008). In different contexts, external economies of scale arise because of the input market in Markusen and Venables (1999) and Jones (2011).

[48] Amiti and Khandelwal (2013) find that decreasing tariffs leads to quality downgrading in sectors and countries that are far below the world technology frontier and upgrading otherwise. See also Amiti and Cameron (2012).

References

[1] Abowd, J., F. Kramarz, D. Margolis (1999), "High Wage Workers and High Wage Firms," *Econometrica*, **67(2)**, 251-333.

[2] Acemoglu, D. (2002), "Directed Technical Change," *Review of Economic Studies*, **69**, 781-809.

[3] Acemoglu, D., and D. Autor (2010), "Skills, Tasks and Technologies: Implications for Employment and Earnings," *Handbook of Labor Economics*, volume 4, part B, O. Ashenfelter and D. E. Card (eds.), Elsevier, Amsterdam, The Netherlands.

[4] Aghion, P., N. Bloom, R. Blundell, R. Griffith, and P. Howitt (2005), "Competition and Innovation: An Inverted U Relationship," *Quarterly Journal of Economics*, **120(2)**, 701-728.

[5] Aghion, P., and R. Griffith (2005), *Competition and Growth: Reconciling Theory and Evidence*, MIT Press, Cambridge, MA.

[6] Aw, B.Y., M. Roberts, and D. Y. Xu (2011), "R&D Investments, Exporting, and Productivity Dynamics," *American Economic Review*, **101**, 1312-1344.

[7] Amiti, M., and L. Cameron (2012), "Trade Liberalization and the Wage Skill Premium: Evidence from Indonesia," *Journal of International Economics*, **87**, 277-287.

[8] Amiti, M., and A. Khandelwal (2013), "Import Competition and Quality Upgrading," *The Review of Economics and Statistics*, **95**, 476-490.

[9] Attanasio, O., P. Goldberg, and N. Pavcnik (2004), "Trade Reforms and Wage Inequality in Colombia," *Journal of International Economics*, **74**, 331-366.

[10] Autor, D. H., L. F. Katz, and A. B. Krueger. (1998) "Computing Inequality: Have Computers Changed the Labor Market?" *Quarterly Journal of Economics*, **113(4)** 1169-1213.

[11] Bernard, A., E. J. Blanchard, I. V. Beveren, and H. Vandenbussche (2012),"Carry-Along Trade," mimeo, Tuck School of Business at Dartmouth.

[12] Bernard, A. B., J. Eaton, J. B. Jensen, and S. S. Kortum (2003), "Plants and Productivity in International Trade," *American Economic Review*, **93**, 1268-1290.

[13] Bernard, A. B., and J. B. Jensen (1995), "Exporters, Jobs, and Wages in US Manufacturing: 1976-87," *Brookings Papers on Economic Activity: Microeconomics,*, 67-112.

[14] Bernard, A. B., and J. B. Jensen (1997), "Exporters, Skill Upgrading and the Wage Gap," *Journal of International Economics*, **42**, 3-31.

[15] Bernard, A. B., J. B. Jensen, S. J. Redding, and P. K. Schott (2007), "Firms in International Trade," *Journal of Economic Perspectives*, **21(3)**, 105-130.

[16] Broda, C., and D. E. Weinstein (2006), "Globalization and the Gains from Variety," *The Quarterly Journal of Economics*, **121(2)**, 541-585.

[17] Burstein, A., J. Cravino, and J. Vogel (2013), "Importing Skill-Bias Technology," *American Economic Journal: Macroeconomics*, **5(2)**, 32-71.

[18] Burstein, A., and J. Vogel (2012), "International Trade, Technology, and the Skill Premium," mimeo, Columbia University.

[19] Bustos, P. (2011a), "The Impact of Trade Liberalization on Skill Upgrading: Evidence from Argentina," mimeo, Universitat Pompeu Fabra, CREI.

[20] Bustos, P. (2011b), "Trade Liberalization, Exports and Technology Upgrading: Evidence on the Impact of MERCOSUR on Argentinian Firms," *American Economic Review*, **101**, 304-340.

[21] Cherkashin, I., S. Demidova, H. L. Kee, and K. Krishna (2012), "Firm Heterogeneity and Costly Trade: A New Estimation Strategy and Policy Experiments," *NBER Working Paper*, # 16557.

[22] Costinot, A. (2009), "An Elementary Theory of Comparative Advantage," *Econometrica*, **77**, 1165-1192.

[23] Das, S., K. Krishna, S. Lychagin, and R. Somanathan (2013), "Back on the Rails: Competition and Productivity in State-Owned Industry," *AEJ Applied*, forthcoming.

[24] Das, S., M. J. Roberts, and J. R. Tybout (2007), "Market Entry Costs, Producer Heterogeneity, and Export Dynamics," *Econometrica*, **75**, 837-873

[25] Davis, S. J., and J. C. Haltiwanger (1991), "Wage Dispersion Between and Within U.S. Manufacturing Plants, 1963-86," *Brookings Papers on Economic Activity: Microeconomics*, **1**, 80-115.

[26] Eaton, J., and S. Kortum (2001), "Trade in Capital Goods," *European Economic Review*, **45**, 1195-1235.

[27] Edwards, S. (2001), *The Economics and Politics of Transition to an Open Market Economy: Colombia*, OECD Publications, Paris, France.

[28] Eslava, M., J. Haltiwanger, A. Kugler, and M. Kugler (2013), "Trade Reforms and Market Selection: Evidence from Manufacturing Plants in Colombia," *Review of Economic Dynamics*, **16**, 135-158.

[29] Faber, B. (2013), "Trade Liberalization, the Price of Quality, and Inequality: Evidence from Mexican Store Prices," mimeo, University of California, Berkeley.

[30] Feenstra, R (2010), *Offshoring in the Global Economy*, MIT Press, Cambridge, MA.

[31] Feenstra, R, G. Hanson (1997), "Foreign Direct Investment and Relative Wages: Evidence from Mexico's Maquiladoras," *Journal of International Economics*, **42**, 371-393.

[32] Feenstra, R, R. Lipsey, H. Deng, A. Ma, and H. Mo (2005), "World Trade Flows: 1962-2000," NBER working paper 11040, Cambridge, MA.

[33] Goldberg, P., J. De Loecker, A. Khandelwal, and N. Pavcnik (2012), "Prices, Markups and Trade Reform,"mimeo.

[34] Goldberg, P., A. Khandelwal, N. Pavcnik, and P. Topalova (2009), "Trade Liberalization and New Imported Inputs," *American Economic Review Papers and Proceedings.*

[35] Goldberg, P., A. Khandelwal, N. Pavcnik, and P. Topalova (2010), "Imported Intermediate Inputs and Domestic Product Growth: Evidence from India," *Quarterly Journal of Economics*, **125**, 1727-1767

[36] Goldberg, P., and N. Pavcnik (2004), "Trade, Inequality, and Poverty: What Do We Know? Evidence from Recent Trade Liberalization Episodes in Developing Countries," *Brookings Trade Forum*, 223-269.

[37] Goldberg, P., and N. Pavcnik (2007), "Distributional Effects of Globalization in Developing Countries," *Journal of Economic Literature*, **45**, 39-82.

[38] Hallak, J. C., J. Sivadasan (2013), "Product and Process Productivity: Implications for Quality Choice and Conditional Exporter Premia," *Journal of International Economics*, **91(1)**, 53-67.

[39] Helpman, E., O. Itskhoki, and S. Redding (2010), "Inequality and Unemployment in a Global Economy," *Econometrica*, **78**, 1239-1283.

[40] Helpman, E., O. Itskhoki, M. Mundler, and S. Redding (2012), "Trade and Inequality: From Theory to Estimation," mimeo, Princeton Univeristy.

[41] Holmes, T. J., and J. A. Schmitz (2010), "Competition and Productivity: A Review of Evidence," *Annual Review of Economics*, **2**, 619-642.

[42] Hummels, D., and A. Skiba (2004), "Shipping the Good Apples Out? An Empirical Confirmation of the Alchian-Allen Conjecture," *Journal of Political Economy*, **112**, 1384-1402.

[43] Jones, C. I. (2011), "Misallocation, Economic Growth, and Input-Output Economics,," *NBER Working Paper*, #16742

[44] Katz, L. F., Murphy, K. M. (1992), "Changes in Relative Wages, 1963-1987: Supply and Demand Factors," *The Quarterly Journal of Economics*, **107**, 35-78.

[45] Khandelwal, A. (2004), "The Long and Short (of) Quality Ladders," *The Review of Economic Studies*, **77(4)**, 1450-1476.

[46] Khandelwal, A., and P. Topalova (2004), "Trade Liberalization and Firm Productivity: The Case of India," *The Review of Economics and Statistics*, **93**, 995-1009.

[47] Kugler, M., and E. Verhoogen (2009), "Plants and Imported Inputs: New Facts and an Interpretation," *American Economic Review Papers and Proceedings*, **99**, 501-507.

[48] Kugler, M., and E. Verhoogen (2012), "Prices, Plants and Product Quality," *The Review of Economic Studies*, **79**, 307-339.

[49] Lee, D., and K. Wolpin (2006), "Intersectoral Labor Mobility and the Growth of the Service Sector," *Econometrica*, **74**, 1-46.

[50] Lileeva, A., and D. Trefler (2010), "Improved Access to Foreign Markets Raises Plant-Level Productivity...For Some Plants," *Quarterly Journal of Economics*, **125**, 1051-1099.

[51] Lora, E. (2001), "Structural Reforms in Latin America: What Has Been Reformed and How to Measure it," Available at SSRN: http://ssrn.com/abstract=909562 or http://dx.doi.org/10.2139/ssrn.909562

[52] Markusen, J., and A. Venables (1999), "Foreign Direct Investment as a Catalyst for Industrial Development," *European Economic Review*, **43**, 335-356.

[53] Melitz, M. (2003), "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity," *Econometrica*, **71**, 1695-1725.

[54] Milgrom, P., and J. Roberts (1990), "The Economics of Modern Manufacturing: Technology, Strategy and Organization," *The American Economic Review*, **80**, 511-528.

[55] Parro, F. (2013), "Capital-Skill Complementarity and the Skill Premium in a Quantitative Model of Trade," *AEJ: Macroeconomics*, **5**, 72-117.

[56] Pavcnik, N. (2002), "Trade Liberalization, Exit, and Productivity Improvements: Evidence from Chilean Plants," *The Review of Economic Studies*, **69**, 245-276.

[57] SCHOTT, P. (2004), "Across-Product versus Within-Product Specialization in International Trade," *Quarterly Journal of Economics*, **119**, 647-678.

[58] THOENIG, M., AND T. VERDIER (2003), "A Theory of Defensive Skill-Biased Innovation and Globalization," *American Economic Review*, **93**, 709-728.

[59] TOVAR, J. (2012), "Consumers Welfare and Trade Liberalization: Evidence from the Car Industry in Colombia," *World Development*, **40**, 808-820.

[60] TREFLER, D. (2004), "The Long and Short of the Canada-US Free Trade Agreement," *American Economic Review*, **94**, 870-895.

[61] TYBOUT, J (2003), "Plant- and Firm-level Evidence on the 'New' Trade Theories," in E. Kwan Choi and James Harrigan, ed., *Handbook of International Trade*, Blackwell Publishing Ltd., Malden, MA.

[62] VERHOOGEN, E. (2008), "Trade, Quality Upgrading and Wage Inequality in the Mexican Manufacturing Sector," *Quarterly Journal of Economics*, **123**, 489-530.

[63] WOOD, A. (1995), "How Trade Hurt Unskilled Workers," *Journal of Economic Perspective*, **9**, 57-80.

[64] YOUNG, ALWYN (2013) "Inequality, the Urban-Rural Gap and Migration," *The Quarterly Journal of Economics*, **129**, 939-993.

A Appendix to section 1, basic model

A.1 Existence in model with no specific inputs

This appendix establishes the conditions under which some domestic firms upgrade their technologies without exporting. Define four cutoffs: cutoff z_1 is the firm that is indifferent between exiting and producing low-tech, $\pi_{H1}(z_1) = 0$; cutoff z_2 is the firm that is indifferent between operating domestically with high and low technology $\pi_{H1}(z_2) = \pi_{H2}(z_2)$, cutoff z_{1x} is the firm that is indifferent between operating domestically and exporting with low-tech $\pi_{H1}(z_{1x}) = \pi_{x1}(z_{1x})$ and cutoff z_{2x} is the firm that is indifferent between operating domestically with low-tech and exporting with high-tech $\pi_{H1}(z_{2x}) = \pi_{x2}(z_{2x})$. Rearranging the expressions for π in section 1.1, we have

$$\begin{aligned}
z_1^{\sigma-1} & \frac{f_1}{\tilde{\sigma} P^{\alpha(\sigma-1)} R} \\
z_2^{\sigma-1} &= \frac{f_2 - f_1}{\tilde{\sigma} P^{\alpha(\sigma-1)} R(\phi - 1)} \\
z_{1x}^{\sigma-1} &= \frac{f_x}{\tilde{\sigma} P^{\alpha(\sigma-1)} R d^{1-\sigma}} \\
z_{2x}^{\sigma-1} &= \frac{f_2 + f_x - f_1}{\tilde{\sigma} P^{\alpha(\sigma-1)} R[\phi(1 + d^{1-\sigma}) - 1]}
\end{aligned}$$

The conditions to assure that some domestically-oriented firms produce low tech and others high-tech are $z_1 < z_2 < \min\{z_{1x}, z_{2x}\}$:

$$z_1 < z_1 \Leftrightarrow \phi f_1 < f_2 \tag{A.1}$$

$$z_2 < z_{1x} \Leftrightarrow f_2 - f_1 < f_x(\phi - 1) d^{\sigma-1} \tag{A.2}$$

$$z_2 < z_{2x} \Leftrightarrow \phi(f_2 - f_1) < f_x(\phi - 1) d^{\sigma-1} \tag{A.3}$$

Condition (A.3) is clearly more restrictive than condition (A.2) since $\phi > 1$. We are then left with (A.1) and (A.3).

A.2 Trade liberalization in model with no specific inputs

Consider a decrease in d or in f_x. Denote with x' the ex post value of variable x. We need to prove that P strictly decreases with the decrease in trade costs. Suppose not.

$$\pi_{H1}(z) = \tilde{\sigma} z^{\sigma-1} P^{\alpha(\sigma-1)} R - f_1$$
$$\pi_{H2}(z) = \phi\tilde{\sigma} z^{\sigma-1} P^{\alpha(\sigma-1)} R - f_2$$
$$\pi_{x1}(z) = (1 + d^{1-\sigma})\tilde{\sigma} z^{\sigma-1} P^{\alpha(\sigma-1)} R - (f_1 + f_x)$$
$$\pi_{x2}(z) = \phi(1 + d^{1-\sigma})\tilde{\sigma} z^{\sigma-1} P^{\alpha(\sigma-1)} R - (f_2 + f_x).$$

Conditional on making the same discrete choice, the profits of firms of any given z (weakly) increase, and the profits of exporters strictly increase. Since firms only change their discrete choice if the new choice yields profits at least as high as the old profits, expected profits must increase. Hence, the free entry condition is violated, and by contradiction P must strictly decrease.

A.3 Existence in model with specific inputs

In the main text, we analyze an equilibrium with three cutoffs $z_1 < z_2 < z_x$, where firms with $z < z_1$ exit, firms with $z \in [z_1, z_2]$ produce low-tech and do not export, firms with $z \in [z_2, z_x]$ produce high-tech and do not export, and firms with $z > z_x$ produce high-tech and export. This appendix shows that there exist parameters such that such equilibrium exists. So, in the main text, we are not analyzing an empty set. For any G with support on $(0, 1)$, take any set of fixed costs and iceberg trade costs such that $\phi^\alpha \sigma_1 f_1 = f_2$ and $f_2 < d^{\sigma-1} f_x$, where $\sigma_1 = \frac{\sigma}{1+\alpha(\sigma-1)} > 1$ is the scalar such that $R = \sigma_1 L$. We claim that there always exists an equilibrium where all firms produce high-tech goods, $z_1 = z_2 < z_x$. Suppose there is, then

$$P = \phi^{\frac{1}{1-\sigma}} P(2)$$
$$\chi(1) = P^{\sigma-1} L \chi(2) \qquad\qquad = \phi P^{\sigma-1} \sigma_1 L.$$

Profits are

$$\pi_{H1}(z) = \tilde{\sigma} z^{\sigma-1} P^{\alpha(\sigma-1)} L - f_1$$

$$\pi_{H2}(z) = \phi^{\alpha} \sigma_1 \tilde{\sigma} z^{\sigma-1} P^{\alpha(\sigma-1)} L - f_2 \tag{A.4}$$

$$\pi_{x1}(z) = (1 + d^{1-\sigma}) \tilde{\sigma} z^{\sigma-1} P^{\alpha(\sigma-1)} L - (f_1 + f_x)$$

$$\pi_{x2}(z) = (1 + d^{1-\sigma}) \phi^{\alpha} \sigma_1 \tilde{\sigma} z^{\sigma-1} P^{\alpha(\sigma-1)} L - (f_2 + f_x). \tag{A.5}$$

Since $\phi^{\alpha}\sigma_1 > 1$ and $\phi^{\alpha}\sigma_1 f_1 = f_2$, then clearly, low-tech is never chosen. It is also simple to check that if $f_2 < d^{\sigma-1} f_x$, the cutoff $z_2 < z_x$ and no firm wants to export low-tech. Now, departing from this equilibrium, decrease f_1 by $\epsilon > 0$ arbitrarily small. A small set of low-tech domestically-oriented firms emerges, but since prices are continuous functions of the cutoffs and mass of firms, and profits are continuous in P, we have an equilibrium such that $z_1 < z_2 < z_x$ as analyzed in the main text. Note that the conditions here are similar to those derived for the model without specific inputs in appendix A.1: In order for such equilibrium to emerge, trade costs must be sufficiently large relative to f_2 and f_1 sufficiently smaller than f_2. The only difference is that here f_1 must not be too much smaller than f_2. Otherwise, the mass of high-tech firms becomes too small and producing high-tech becomes excessively expensive.

A.4 Price indices in model with specific inputs

In the model with specific inputs, price indices are implicitly defined as a function of the mass of firms M_e and cutoffs z_1, z_2 and z_x as

$$P(1) = \mu M_e^{\frac{1}{1-\sigma}} P^{1-\alpha} \left[\int_{z_1}^{z_2} z^{\sigma-1} dG(z) \right]^{\frac{1}{1-\sigma}},$$

$$P(2) = \left\{ \mu M_e^{\frac{1}{1-\sigma}} \left[\int_{z_2}^{\infty} z^{\sigma-1} dG(z) + d^{1-\sigma} \int_{z_x}^{\infty} z^{\sigma-1} dG(z) \right]^{\frac{1}{1-\sigma}} \right\}^{\frac{1}{\alpha}},$$

where $P = [P(1)^{1-\sigma} + \phi P(2)^{1-\sigma}]^{\frac{1}{1-\sigma}}$.

B Data: Within- versus across-sector patterns

This appendix shows that most variation in firm characteristics in the data occur within sectors, and that sectors exhibit similar systematic variations. Our empirical analysis bundles all manufacturing plants ignoring sectoral classifications. As explained in section 3, this approach would be problematic if sectors were very different or if they underwent different experiences during the trade liberalization. Then, firms that source or provide inputs to different sectors would be differentially affected by trade. But in line with the literature, we show here that, in the 1988 cross-section, (i) most variations in firm-characteristics occur within sectors, and that (ii) the correlations that we exploit in the aggregate data occur systematically within sectors. Between 1988-1994, (iii) most changes in firm characteristics occurred within sectors, and (iv) sectors experienced similar systematic changes.

C Counterfactual shifts in white-collar shares

We reconcile counterfactual shifts in the distribution of white-collar shares with its aggregate changes on table 13. The relevant sections of the table are copied on table C.1 for easier reference:

Table C.1: Changes in distribution of white-collar shares

	percentiles					
	10%	25%	50%	75%	90%	**total**
NSI model	-0.2	-0.2	-0.2	-0.2	-0.2	**0.03**
SI model, elastic labor	0.4	1.8	4.1	3.7	3.0	**5.6**
SI model, inelastic labor	-2.4	-3.0	-2.1	-1.3	-0.7	**0**

In all specifications of the model, shifts in percentiles are smaller than the total. This appendix uses the example of the SI model with inelastic labor to explain how shifts in employment, from the less to the more skill intensive firms can generate this result. Table C.2 partitions firms by quartiles of white-collar shares. It reports the share of white-collar workers and the share of employment in each quartile before and after the counterfactual. The sum of the product of lines (A) and (B) yields the total share of white-collar workers before the trade liberalization, 0.34. The sum of the products of lines (C) and (D) is the total share of white-collar workers post-liberalization, which with inelastic labor is also 0.34. The sum of employment shares in lines (B) and (D) is 100%. The last two lines report the difference between pre- and post-liberalization. Line (E) shows that the white-collar shares decreased in all quartiles of the distribution, as on table C.1. This result is explained through line (F): Employment shares shift from less to more skill-intensive firms.[49]

Table C.2: Decomposition of changes in skill intensity

	quartiles of white-collar shares				
	1	2	3	4	**total**
before liberalization					
avg. share of white-collars (A)	0.11	0.22	0.34	0.60	**0.34**
share of employment (B)	0.10	0.29	0.40	0.22	**1.00**
after liberalization					
avg. share of white-collars (C)	0.08	0.19	0.33	0.60	**0.34**
share of employment (D)	0.10	0.23	0.43	0.24	**1.00**
Δ = after - before					
avg. share of white-collars (E) = (A) - (C)	-0.03	-0.03	-0.01	-0.001	**0.00**
share of employment (F) = (B) - (D)	-0.004	-0.05	0.03	0.03	**0.00**

Bustos (2011), Kugler and Verhoogen (2012) and Pavcnik (2002) provide evidence that ex-ante larger firms grow and invest in product and process innovation relative to other firms following a trade liberalization. Since larger firms are typically more skill intensive, these findings are consistent with shifts in employment on table C.2. But these shifts do not appear in the Colombian data—neither in aggregate manufacturing nor systematically in the various sectors, possibly because of large errors in our measure of skills and because we look at the raw data without controls and interactions with tariff cuts that the papers cited above use.

D Robustness: Fixed parameters

This appendix checks the robustness of the model with respect to fixed parameters. Cross-sectional moments are not presented because they were almost unchanged for all experiments.

[49] This result is analogous to the effect of trade on a skill abundant country in a standard factor-proportions model: The skill intensity decreases in all sectors and the relative production of skill intensive goods increases.

Table D.1: Parameter estimates (est) and standard errors (se)

parameter	benchmark*		$\alpha = 0.5$		$\sigma = 2$		$\sigma = 7$	
	est	se	est	se	est	se	est	se
Stage 1								
μ_1	-0.11	0.02	-0.06	0.02	-0.08	0.04	-0.10	0.01
σ_1	0.69	0.01	0.68	0.01	1.4	0.01	0.57	0.01
σ_2	3.6e-3	1.7e-3	4.8e-3	9.9e-4	1.1e-2	2.3e-3	1.9e-3	5.3e-4
f_1	1.4e-3	3.0e-4	1.9e-3	3.6e-4	3.0e-3	5.5e-4	1.1e-3	2.0e-4
f_2	1.4e-4	5.0e-5	1.8e-4	4.2e-5	2.2e-4	5.3e-5	7.3e-5	2.2e-5
μ_M	-3.4	0.05	-2.7	0.06	-2.6	0.05	-3.9	0.08
σ_M	1.5	0.06	1.3	0.07	1.4	0.04	1.3	0.04
μ_X	-0.17	0.09	-0.03	0.05	0.14	0.04	-0.86	0.03
σ_X	1.9	0.05	1.8	0.08	1.7	0.05	1.7	0.04
Y^*	0.19	0.03	0.24	0.03	0.10	0.01	0.24	0.03
T^*	3.7	0.06	3.6	0.07	3.8	0.04	4.3	0.06
τ^*	10.9	0.09	12.0	0.05	10.4	0.77	10.5	0.05
Stage 2								
w_s/w_u	2.43	0.21	2.43	0.21	2.39	0.21	2.46	0.17
σ_π	0.18	0.01	0.18	0.01	0.18	0.01	0.18	0.01
l_1	-4.8	0.06	-4.8	0.06	-3.6	0.08	-5.5	0.04
l_2	2.9	0.60	2.9	0.71	2.5	0.59	3.3	0.68

* benchmark $\alpha = 0.7$ and $\sigma = 5.0$.

Here, we experiment with changes in α and in σ used in the first stage. Appendix D.1 experiments with changes in σ_L and in fixed costs that affect only the counterfactual with inelastic labor supply. All these results focus exclusively on the SI model. Appendix D.2 shows the results of the NSI model when we change parameter f_3 governing the convexity in labor costs.

The counterfactual results from increasing he labor share from the benchmark $\alpha = 0.7$ to $\alpha = 0.5$ are in section 6 under alternative A3, and the parameter estimates are on table D.1. In the benchmark, the elasticity of substitution is $\sigma = 5.0$, the mean of elasticities in Broda and Weinstein (2004) for three-digit product categories. We experiment here with $\sigma = 2.0$ corresponding to the median elasticity in Broda and Weinstein and $\sigma = 7$. The parameter estimates on table D.1 do not change much. The only substantial change in the cross-section is in the fixed costs. These costs reflect the expected profits from entering, mporting and exporting. Since a lower elasticity of substitution implies that gross profits are a higher share of sales, the estimated fixed costs nearly double when $\sigma = 2.0$ relative to the benchmark $\sigma = 5$.

Table D.2 summarizes counterfactual results when labor is perfectly elastic. The partition of firms according to their participation in international trade, and the change in their sales is very similar in all cases, $\sigma \in \{2, 5, 7\}$. When σ is low, firms' technology choices are more interdependent, since a high-technology firm cannot disregard a lot of low-tech varieties and concentrate its input purchases only on a few high-tech varieties. This tighter interdependence, on the one hand, implies that technology upgrading is more widespread because domestically-oriented firms respond more to changes in importers' and exporters' technologies. As we go down the columns of table D.1 and σ increases, the share of domestically-oriented firms upgrading technologies goes from 83% when $\sigma = 2$ to 37% when $\sigma = 5$ (benchmark) to 20% when $\sigma = 7$. On the other hand, the tighter interconnection implies that technology upgrading among importers and exporters is smaller because these firms still source a significant share of their inputs from lower-technology domestic varieties. The change in skill intensity among the largest firms, continuing exporters increases in σ—it goes from 3.2% points when $\sigma = 2$ to 5.9% points when $\sigma = 5$ (benchmark) to 6.4% points when $\sigma = 7$. Because these firms weight a lot in the aggregate, aggregate manufacturing skill intensity increase by less when $\sigma = 2$. It increases by from 15% to 22%, 7.1% points, when $\sigma \in \{5, 7\}$ and from 16% to 21%, 5.1% points, when $\sigma = 2$.

In contrast, when labor is inelastic, manufacturing changes in the skill premium are larger when $\sigma = 2$ precisely because these changes need to be large enough to lead domestically-oriented firms to downgrade their technologies and hence their demand for skilled workers. The skill premium increases by 11% when $\sigma = 2$, by 2.7% when $\sigma = 5$ in the benchmark and by only 0.9% when $\sigma = 7$. It is unclear which elasticity best reflects the data. Broda and Weinstein (2004) obtain their estimates from finely-defined product categories in trade data. On the one hand, one may think that the elasticity of substitution is lower in our data where all manufacturing goods are aggregated. On the other hand, one might plausibly think that varieties produced in different countries are less easily substitutable from varieties from the same country. Last, their estimates rely on the assumption that price differences do not reflect differences in quality or other technological improvements, which are innate to our model.

Table D.2: Summary of counterfactual by participation in international trade

	domestic oriented	continuing importers	continuing exporters**	new importers†	new exporters**	all firms
benchmark: $\sigma = 5$ (similar when $\sigma = 2$ or 7)						
share of firms	65%	19%	12%	3.1%	0.5%	100%
log change in sales	-0.26	-0.20	-0.14	-0.07	0.08	-0.17
initial skill intensity	4.1%	15%	19%	5.9%	14%	15%
$\sigma = 2$						
share of firms upgrading	83%	100%	100%	100%	100%	89%
change in skill intensity*	1.4%	8.1%	3.2%	12.0%	20.7%	5.1%
$\sigma = 5$ **(benchmark)**						
share of firms upgrading	37%	94%	100%	99%	100%	57%
change in skill intensity*	2.1%	8.7%	5.9%	18.7%	11.4%	7.1%
$\sigma = 7$						
share of firms upgrading	20%	99%	100%	99%	100%	45%
change in skill intensity*	0.4%	8.7%	6.4%	18.6%	12.0%	7.1%

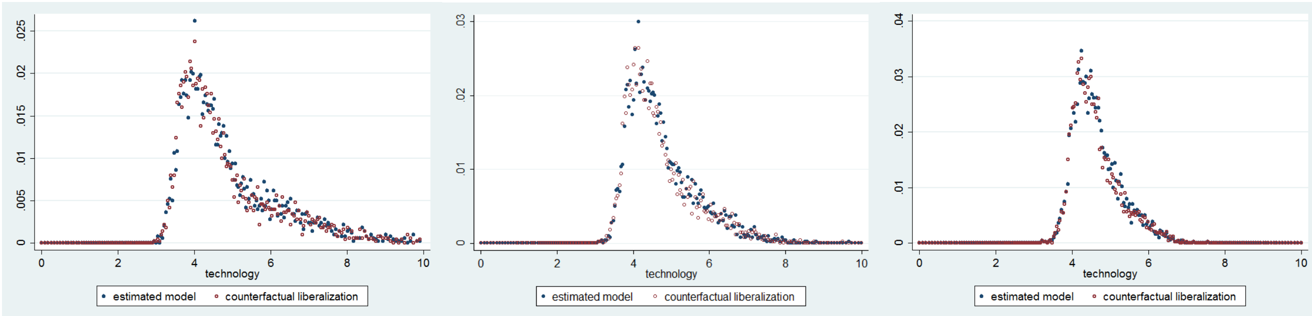
* Change in skill intensity is in percentage points, final minus initial.

** includes firms that import and export.

† includes firms that initially export only and start importing with the counterfactual.

D.1 Fixed parameters & inelastic labor supply

The assumption that fixed costs use some factor with perfectly elastic supply implies that these costs do not change with the counterfactual or with changes in wages. This assumption is innocuous if labor is elastic because wages do not change anyway. But in the counterfactual with inelastic labor, average wages decrease by 15% on average. Allowing all fixed costs to decrease with wages, makes it cheaper for firms to upgrade their technology, but the increase in the skill premium during the liberalization increases only from 2.7% to 2.8%. The elasticity of substitution between skilled and unskilled workers σ_L again has no effects on the results if labor is elastic, but if labor is inelastic, the higher the elasticity, the smaller the change in skill premium needed to clear the labor market after the liberalization. Values for σ_L in the literature are $\sigma_L = 1.1$ in Lee and Wolpin (2006), $\sigma_L \in [1.6, 1.8]$ in Acemoglu and Autor (2010) and $\sigma_L = 1.4$ in Katz and Murphy (1992). The predicted change in the skill premium in the counterfactual trade liberalization is 2.7% if $\sigma_L = 1.1$, 2.7% if $\sigma_L = 1.6$ (benchmark), and 2.6% if $\sigma_L = 1.8$. So, again, the results barely change with σ_L.



(a) $f_3 = 7$ (b) benchmark: $f_3 = 10$ (c) $f_3 = 15$

Figure 9: Distribution of technology choices, NSI model

D.2 NSI model: Fixed cost parameter f_3

This appendix checks for the robustness of results with respect to parameter f_3 in the parametrization of the fixed costs of the NSI model, in section 4.1.1:

$$f(\tau) = f_1 + f_2 \tau^{f_3}.$$

In the main text, we fix $f_3 = 10$, and we present here the results from $f_3 = 7$ and $f_3 = 15$. Recall that the convexity generated by f_3 is important for technology choices to be contained within the grid $\tau \in [0, 10]$ even when firm's productivity $z(\tau, \omega)$ increases with τ. Figure 9 illustrates the density of technology choices. As f_3 increases, technology choices become more concentrated. But in all three cases, technology choices barely change with the counterfactual with perfectly elastic labor supply. All non-exporters downgrade technology and aggregate skill intensity increases by a mere 0.2%. Table D.3 displays technology parameters. Parameters of the first stage are very similar in all cases, except for parameter f_2 that needs to adjust to account for changes in f_3. Parameters of the second stage change slightly to account for differences in the distribution of technology choices.

E Multiple equilibria and Monte Carlo simulations

There is a coordination element to the model: As some firms increase their output quality, they increase other firms' incentives to increase quality. We cannot rule out multiplicity of equilibria,

Table D.3: Parameter estimates in the NSI model with $f_3 = 7, 10, 15$

	benchmark: $f_3 = 10$		$f_3 = 7$		$f_3 = 10$	
parameter	estimate	std. error	estimate	std. error	estimate	std. error
Stage 1						
μ_1	-0.31	0.02	-0.31	0.02	-0.31	0.02
σ_1	0.68	0.01	0.67	0.01	0.68	0.01
σ_2	2.8e-3	1.9e-4	3.0e-3	2.2e-4	2.3e-3	2.9e-4
f_1	2.3e-3	3.2e-4	2.6e-3	3.3e-4	2.3e-3	2.9e-4
f_2	4.4e-11	1.0e-11	6.3e-9	3.1e-11	1.5e-14	5.3e-15
μ_M	-3.6	0.12	-3.5	0.14	-3.6	0.12
σ_M	1.4	0.09	1.4	0.08	1.4	0.09
μ_X	0.25	0.31	0.26	0.23	0.26	0.22
σ_X	1.9	0.08	1.9	0.04	1.9	0.08
Y^*	0.54	0.01	0.53	0.01	0.54	0.01
T^*	3.8	0.46	4.2	0.60	3.8	0.58
Stage 2						
w_s/w_u	2.42	0.18	2.37	0.17	2.41	0.18
σ_π	0.18	0.01	0.18	0.01	0.18	0.01
l_1	-5.6	0.13	-6.0	0.18	-5.2	0.09
l_2	1.26	0.26	0.91	0.18	1.79	0.35

but it is unlikely that they exist at least for the parameter estimates. As described in section **??**, for each set of parameters, we iterate over firms' choices of quality and participation in international trade until no firm wants to change its choices. To check for multiple equilibria given the parameter estimates, we randomize over firms initial choices 1,000 times and see if their choices converge to the same point. In all 1,000 experiments the choices of all 5,000 remained the exactly same.

In estimating the model, we simulate the behavior of 5,000 firms. For each parameter guess, we transform a *fixed* vector of random variables to get each firm's productivity $z(q, \omega)$ and costs $f_M(\omega)$ and $f_X(\omega)$. The number of firms was chosen due to computational constraints, but to assess whether the number is large we change the vector of random variables forty times and re-run the optimization algorithm. If 5,000 is sufficiently large, the results should not change much. About 60% of the parameter estimates are within 99% confidence interval of the original estimates. The parameters that are worse identified are Q^*, q^* and μ_M. When the random draws change, the distribution of quality choices change and q^* and Q^* need to change accordingly.

Our parameter estimates also imply a large variance in firms fixed importing costs. So, it is also natural that the mean cost is not well identified. The counterfactual results change the increase in skill intensity varies by about one percentage point, but there is no qualitative change. The results do not change at all if we double the number of quality choices $q \in [0, 10]$ from 200 to 400 or if we expand the choice set beyond the upper bound of $q = 10$.

We also conduct Monte Carlo simulations. We generate data with random parameters drawn from a uniform distribution with support of four standard deviations from the original parameter estimates. For each generated data set, we run our simulation algorithm to recover the original parameters. We repeat this exercise 100 times, and find that the parameter estimates are within two deviations of the original estimates 80% of the time and that the median deviation is just 0.67 times standard errors, showing that the parameters are reasonably well identified.[50]

[50] To get our parameter estimates, we ran two algorithms, a simulated annealing and a simplex algorithm, but for these Monte Carlo experiments, we only run the simulated annealing. Identification would probably be even better if we had automated the process and ran also the simplex algorithm.