

The Impact of Trade on Technology and Skill Upgrading

Evidence from Argentina

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Abstract

In the last 20 years, wage inequality has increased in many developing countries. Most research on this topic focuses on two alternative causes: trade or skill-biased technical change. Several empirical studies in both developed and developing countries document increases in skill intensity within all sectors, favoring the technological change explanation over trade. Instead, I present and test a model where bilateral trade liberalization increases exporting revenues inducing more firms to enter the export market and to adopt skilled-biased new technologies. I find that the increase in the relative demand of skilled labor does not come from labor reallocation across sectors or firms but from skill upgrading within firms. Firms that upgrade technology faster also upgrade skill faster. Finally, firms entering the export market after liberalization become more skill and technology-intensive than non exporters.

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1 Introduction

In the last 20 years, wage inequality has increased in many developed and developing countries. Most research on this topic focuses on two possible causes, trade or skill-biased technical change. The evidence suggests that the main cause of the rising skill premium has been skill-biased technical change, with trade playing a minor role. An open question remains on the effects of trade on technology adoption and its effects on skill upgrading through that particular channel.

The view that the rise in skill premia is caused by technological change is partly founded in empirical studies that contradict the predictions of the Heckscher-Ohlin (H-O) trade model: when a skill-abundant country opens up to trade, the relative price of skill-intensive goods increases and production shifts towards skill-intensive sectors, increasing the relative demand for skilled labor and the skill premium; conversely, trade opening in skill-scarce developing countries would lead to a reduction in the skill premium.

In the United States, where there has been a sharp increase in the skill premium in the last 20 years, the relative price of skilled-labor-intensive goods has not increased (Lawrence and Slaughter, 1993). Most of the increase in the relative demand of skilled labor has occurred within manufacturing sectors, with only a minor part being explained by the expansion of skill-intensive sectors (Berman, Bound and Griliches, 1994). The finding that all sectors increased their relative demand for skilled labor and that the rate of skill upgrading has been greater in computer-intensive industries (Autor, Katz and

Krueger, 1998) suggests that skill-biased technical change has played a more important role than trade.¹

In addition, several empirical studies document a considerable increase in the skill premium after trade liberalization in developing countries like Brazil, Chile, Colombia and Mexico.² In the case of Argentina, after trade was liberalized in the early 1990's, the college wage premium increased 10 percentage points per year, while it had been stable in the 1980's (Galeani et al., 2003). In these countries the share of skilled workers has also increased within most industries. These empirical findings are also consistent with the view that skill-biased technical change is the cause of widening wage inequality, and are hard to reconcile with the predictions of the H-O model.³

I follow a different theoretical perspective that looks at the interplay of technological change and trade liberalization. Acemoglu (1998, 2003) suggests that the empirical findings for the U.S. are consistent with globalization as the root cause of widening wage inequality if growing trade increases the skill-bias of technical change in

¹ Feenstra and Hanson (1996, 1999) argue that when trade in intermediate inputs is introduced in a H-O framework, increased trade can cause skill upgrading within 4-digit industries.

² See Pavcnik et al. (2004) on Brazil, Gindling and Robbins (2001) on Chile and Costa Rica; Attanasio et al. (2004) on Colombia, Hanson and Harrison (1999) on Mexico.

³ The increase in the skill premium in Latin American countries can be reconciled with the H-O framework if unskilled-labor-intensive industries were relatively more protected prior to liberalization, or if the countries also open up to trade with more unskilled-labor-abundant countries like China. These explanations would still work through reallocations of labor towards skill-intensive sectors, and are not consistent with the evidence for Colombia and Mexico. In the first country, Attanasio et al. (2004) find no evidence of labor reallocation across sectors, and find that changes in skill premiums cannot be related to changes in tariffs across sectors. Feliciano (2001) finds similar results for Mexico, and Verhoogen (2004) reports employment shifts towards unskilled-labor-intensive industries, coincident with rising skill premia. Feenstra and Hanson (1996, 1997) develop a model that accounts for the simultaneous increase in the skill premium in a developed and a developing country when they open up to trade, introducing capital movements and trade in intermediate inputs, explaining the increase in the relative demand for skilled labor within sectors. Antras et al. (2005) present a model where globalization leads to the formation of hierarchical teams across countries, leading to higher wage inequality in developing countries as higher ability workers form teams with managers in developed countries.

skill-abundant countries. Yeaple (2005) shows that increased export opportunities make adoption of new technologies profitable for more firms, thus increasing the aggregate demand of skilled labor and the skill premium.

This paper presents simple model where trade and capital account liberalization increase the profitability of new technologies and the relative demand for skilled labor in developing countries, and tests its predictions in the context of the trade and capital account liberalization in Argentina in the early 1990s.

The model builds on work by Melitz (2003) and Yeaple (2005), departing from the H-O framework by introducing increasing returns to scale and monopolistic competition, as in Krugman (1979, 1980), and by focusing on within sector firm heterogeneity rather than differences in skill intensity across sectors. Firms are heterogeneous in an underlying productivity parameter (which can be interpreted as managerial ability), and can choose to adopt a lower marginal cost new technology, after paying a fixed cost. Within each sector, only the most productive firms enter the export market and thus make enough profits to pay the higher fixed costs of adopting the new technology. Trade liberalization reduces variable export costs, increasing exporting revenues and inducing more firms to enter the export market, which makes adoption of new technologies profitable for more firms. In addition, it reduces the cost of adoption of new technologies through the elimination of tariffs on imported capital goods and restrictions on technology transfers, making adoption profitable for more exporters. Capital account liberalization in a capital scarce country reduces the interest rate, further lowering the cost of investment in new technologies. Adoption of skill-intensive new technologies increases the relative demand for skilled labor and the skill premium. But

because this affects all sectors, the effect of trade cannot be identified through variation across sectors. This can rationalize the small effects of trade found in empirical studies with sector-level data. Instead, I study heterogeneous responses to trade and capital account liberalization of firms within sectors.

I analyze a new panel of Argentinean manufacturing firms covering the period 1992-1996. An advantage of this data set is that it includes information on the educational level of workers, while standard industry surveys and census only classify workers into production (P) and non-production (NP) occupational categories. An additional new feature of this data set is that it permits to build a comprehensive measure of technology upgrading, as it includes several dimensions of adoption of new technologies such as spending on high tech capital goods, computers and software; payments for technology transfers and patents; and spending on equipment, materials and labor related to innovation activities performed within the firm.⁴

In a preliminary analysis of the data, I find that the equilibrium relative demand of skilled labor increased 17% in the period 1992-1996.⁵ Galeani et al. (2003) report that in the same period the skill premium was growing at an average of 7 percentage points per year in the industrial sector, indicating that the rise in the equilibrium relative demand of skilled labor must come from a demand shift.

⁴ Such as R&D, adaptation of new products or production processes, technical assistance for innovations in production, organization, commercialization, engineering and industrial design.

⁵ The equilibrium relative demand for skilled labor is measured as the ratio of skilled workers divided by unskilled workers. Skilled workers are college graduates plus tertiary education graduates converted to college equivalents using the 1992 college wage premium. Unskilled workers are primary school graduates and high school graduates converted to primary school equivalents using the 1992 high school wage premium. As in both years workers are weighted by the 1992 wage premium, measured changes in the equilibrium relative demand of skilled labor only reflect changes in quantities, and not in prices.

Out of the 17 percentage points increase in the equilibrium relative demand of skilled labor in the period 1992-1996, 15 percentage points are explained by skill upgrading within P, NP and R&D occupational categories, and only 2 percent by reallocations of labor from P towards NP and R&D. This evidence suggests that previous studies that have used P and NP as a proxy for unskilled and skilled labor might be underestimating the degree of skill upgrading. Additionally, I find that the increase in relative demand of skilled labor does not come from labor reallocation across sectors, nor across firms, but from skill upgrading within firms. This evidence points towards technology upgrading within sectors and firms as the main cause of the increase in the relative demand of skilled labor. Therefore, my empirical work focuses on investigating the effects of trade and capital account liberalization on technology adoption and its effects on skill upgrading through that particular channel.

In the model, initial heterogeneity determines differential firm-level responses to liberalization. The model has predictions both in terms of levels and changes in technology spending after liberalization for firms of different initial productivity: continuing exporters (firms that exported both before and after trade liberalization), new exporters (firms that started exporting after liberalization) and never exporters (firms that did not export before nor after liberalization). I test the following five predictions of the model: first, as the only firms using the new technology before liberalization are the most productive continuing exporters, observed skill intensity before liberalization is higher only for this group; second, continuing exporters and the most productive new exporters have a discretely higher level of spending on technology after trade liberalization; third and fourth, the change in technology spending and skill upgrading after trade

liberalization has an inverted U shape, being highest for firms in the middle range of the productivity distribution (new exporters and the least productive continuing exporters); finally, firms that upgrade technology faster also upgrade skill faster.

The survey also contains information on the sources of financing technology spending that indicates that financial underdevelopment poses constraints on the optimal technology choices predicted by the model, especially for small and home-owned firms. In the context of the model, the presence of credit constraints coupled with fixed costs of technology adoption imply that foreign-owned firms are more likely to be able to finance investment in technology.

When taking the predictions of the model to the data, I test for discrete differences between continuing exporters, new exporters, foreign-owned firms and domestically-owned never exporters, both in levels and changes in technology spending and skill intensity. I find that, within each 4-digit-SIC industry, continuing exporters and foreign-owned firms were more skill-intensive than domestically-owned never exporters prior to liberalization. Firms which started exporting after liberalization were not initially more skill-intensive than never exporters, but upgraded skill faster after trade liberalization. I also find that new exporters, continuing exporters and foreign-owned firms spend 53% to 69% more in technology than domestically-owned never exporters after trade liberalization, controlling for 4-digit-SIC industry, initial productivity and initial size. Moreover, new exporters upgrade technology faster than other firms. Finally, I show that firms that invest more in technology upgrading also upgrade skill faster, where one standard deviation in the change in technology spending explains 38% of the average increase in the share of skilled labor.

The next section describes the trade and capital account liberalization in Argentina. Section 1.3 describes the data set. Section 1.4 provides preliminary empirical evidence on the increase in the relative demand for skill. Section 1.5 develops the theoretical model and derives the empirical predictions on the effects of trade and capital account liberalization on within firm skill and technology upgrading. Section 1.6 describes the broad patterns in the data, presents the empirical strategy and tests the predictions of the model. Section 1.7 concludes.

2. Trade and Capital Account Liberalization in Argentina

At the beginning of the 1990's, Argentina undertook a broad reform program that included trade and capital account liberalization. Trade liberalization was implemented first through unilateral policies, and was later complemented by regional trade liberalization through the MERCOSUR treaty, and the multilateral negotiations of the General Agreement on Tariffs and Trade (GATT).

Trade liberalization started as a unilateral policy in 1988, as the result of negotiations started in the context of structural reforms supported by the World Bank. The objective of these first steps towards reform was to reduce the scope of non-tariff barriers,⁶ which had been the main trade policy instrument in the period 1982-1988.

⁶ In the 1980's, the NTB were implemented through a system of licenses and previous authorizations that regulated entry of all goods. The authorizations were organized in four lists:

1. Prohibited imports (10% of tariff positions): sumptuary consumption goods and industrial intermediate goods produced locally.
2. Imports requiring previous authorization (40% of positions) : capital goods and industrial intermediate goods, in practice, authorization was denied if there was local production.
3. Medical and pharmaceutical products (8% of positions).
4. Rest of imports: mainly products not produced locally, in this case authorization was required but given automatically.

There was also a gradual reduction in import tariffs and surtaxes,⁷ which implied a lower level of protection for the intermediate and capital goods industries.⁸

Between October 1988 and October 1991, there were 11 major revisions of tariff and non-tariff barriers, many times related to changes in macroeconomic policy aimed at controlling hyperinflation. As a result of macroeconomic and trade policy instability during this period, trade liberalization had an impact only after 1991, when the convertibility plan was launched. By October 1991, the average nominal tariff was 12%, ranging from 0% for capital goods not produced in the country to 22% for consumption goods. Almost all import licenses and quotas were eliminated, with the exception of the automobile industry.

After 1991 most export taxes were also eliminated, and in 1992 there was an increase in tax rebates for exports, increasing the average from 3.3% to 6.3% of the value of exports. The program also included other measures that affected trade like reforms on customs administration and port activity, and the reintroduction of the temporary admissions regime.

MERCOSUR was established by Argentina, Brazil, Paraguay, and Uruguay in 1991 with the Treaty of Asuncion. The agreement included the progressive elimination of the tariff and non-tariff restrictions to the circulation of merchandises, the adoption of a common external tariff and a common trade policy with third countries.

⁷ In 1985 the nominal tariff average was 37%. Protection was higher for final goods, around the mean for capital goods and lower for intermediate goods. There was differential treatment for goods produced in the country.

⁸ In 1987 nominal average tariffs on capital goods produced in the country was 48% and 12% if not produced in the country.

There was a transition phase between 1991 and 1994 that consisted of progressive tariff reductions aimed to achieve free trade within the region by the end of 1994. The Customs Union was established in 1995 with the adoption of a Common External Tariff (CET), with an average level of 11%. Tariffs varied between 0 and 20% across industries. Inputs and materials had the lowest tariffs, followed by semi-finished industrial goods, and final goods. There were exceptions to internal free trade for a limited number of products, and special regimes for sugar and automobiles and some products faced tariff rates different from the CET. As a result of the agreement, in 1996 the import weighted average intra-MERCOSUR tariff was 0.86% for Argentina and 0.02% for Brazil, while the extra-zone average tariff was 13.17% and 15.44% respectively.

Trade liberalization had a strong impact on trade flows. Between 1991 and 1999 imports grew at an average rate of 13.6% per year and exports at an average rate of 10.5%. While imports from MERCOSUR grew at a similar rate than those from the rest of the world (14.3%) exports grew twice as much (20.8%).

At the same time, different measures were undertaken towards capital account liberalization. In 1989 all restrictions on entry and exit of foreign capital were eliminated, along with the requirement of previous authorization for Foreign Direct Investment (FDI). Equal treatment of foreign and national capital was guaranteed by law. In 1991, the Convertibility Law established a fixed parity between the peso and the dollar, and the commitment of the Central Bank to sell and buy currency at that parity. The plan also authorized deposits, debt and contracts to be denominated in dollars establishing a bi-monetary system that eliminated all restrictions on the use of foreign currency.

There was a considerable growth of FDI during the 1990's. The stock of FDI as a share of GDP increased from 7.7% in 1992 to 22.2% in 1999. FDI flows to the manufacturing sector increased from US\$ 758 million per year in the period 1992-1993 to US\$ 2,266 million in 1994-1996, and US\$ 3,461 million in 1997-1999.

3. Data

The data I analyze comes from the Survey on Technological Behavior of Industrial Argentinean Firms [Encuesta sobre la Conducta Tecnologica de las Empresas Industriales Argentinas (ETIA)] conducted by the National Institute of Census and Statistics in Argentina (INDEC). The survey covers the period 1992-1996 and was conducted in 1997 over a representative sample of 1,639 industrial firms. The sample was based on 1993 census data and covers 54% of total industrial sales, 50% of employment and 61% of exports in 1996.

As the survey was conducted in 1997, it does not contain information on firms that were active in 1992 and exited afterwards. I focus my analysis on a balanced panel of 1,516 firms present both in 1992 and 1996.⁹ The lack of information on entry and exit poses some limitations on the analysis of reallocations across firms and industries, but as the balanced panel sample still represents 44% of industrial sales, the results can be interpreted as highly indicative of the overall pattern of reallocations.

The initial year in the data is 1992, and the major trade and capital account liberalization measures were taken in October 1991. Still, the data for 1992 can be a good

⁹ The total number of firms present both in 1992 and 1996 is 1519, but three of them report values of changes in skill intensity that are outliers (they are from 8.26 to 11.7 standard deviations from the mean) thus they are excluded from the analysis.

indication of the situation before liberalization started to have a considerable impact on technology adoption. Between October 1988 and October 1991 there were 11 major revisions on trade policy and a similar number of revisions in macroeconomic policy, as policymakers attempted to stop hyperinflation. The extreme instability of the previous period brought a high degree of uncertainty on whether the reforms taken at the end of 1991 would be permanent. Then, even if liberalization started having an impact in 1992, many investment decisions are very likely to have been delayed until the reform was perceived as permanent.¹⁰ When analyzing the data, I use 1992 as an indicator for the situation before liberalization had a significant impact, and 1993-1996 as the period after liberalization.

3.1 Education Level of Workers

An important advantage of this survey over standard industrial surveys and censuses is that it contains direct information on the educational level of workers. Table 1.1 reports the change in employment by educational categories between 1992 and 1996. This change is ordered by skill, with employment of engineers growing 11% while employment of high school and primary school workers fell 9%.

¹⁰ For instance, FDI flows to the manufacturing sector increased from US\$ 758 million per year in 1992-1993 to US\$ 2,266 million per year in 1994-1996. Imports of capital goods in the manufacturing sector also accelerated after 1992. In 1991 they were only slightly above the average for the period 1987- 1990, representing 1.9% of Industrial GDP. They started increasing in 1992 when they became 3.2% of industrial GDP, and continued growing to reach 4.8% in 1996.

Table 1.1
Industrial Employment by Education

	1992	1996	Absolute change	Percent change
Total employees	331,438	308,339	-23,099	-0.07
<u>Educational categories</u>				
Engineers	8,632	9,590	958	0.11
Other college	15,626	16,251	625	0.04
Tertiary	24,226	25,816	1,590	0.07
High school + Primary school	282,954	256,682	-26,272	-0.09

Table 1.2
Relative Employment of Skilled Labor

	1992	1996	Absolute change	Percent change
College Equivalents (S)	42,893	45,699	2,806	0.07
Primary Equivalents (U)	322,526	293,471	-29,055	-0.09
Skilled / Unskilled	0.13	0.16	0.02	0.17

Note: The source of the data is ETIA balanced panel of 1516 firms. In Table 1.1.2 educational categories are weighted by the 1992 wage premiums from Galeani and Sanguinetti (2003) and Gasparini et al (2002).

I aggregated workers into two skill categories to obtain a measure of the equilibrium relative demand of skilled labor (S/U):

$$\frac{S}{U} = \frac{L_{college} + L_{tertiary} \frac{w_{college}}{w_{tertiary}}}{L_{primary} + L_{high\ school} \frac{w_{higschool}}{w_{primary}}}$$

Skilled workers (S) are college graduates plus tertiary education graduates converted to college equivalents.¹¹ Unskilled workers (U) are primary school graduates

¹¹ College graduates completed 5 to 6 years of education after high school, while tertiary graduates completed 3 years of education after high school.

plus high school graduates converted to primary school equivalents.¹² This aggregation scheme corresponds to the situation where workers within skill categories are perfect substitutes, and is a good approximation when the elasticity of substitution is higher within than across categories. This seems to be a reasonable assumption, as the increase in employment of college graduates and tertiary education graduates increased by the same amount (6,5 %) while employment of high school and primary school workers fell by 9%. The conversion of workers to college and primary school equivalents was done using the 1992 industrial sector wage premia.¹³ Then, reported changes in the relative demand of skilled labor reflect changes in employment and not in wages. Overall, the relative employment of skilled labor increased by 17% in the balanced panel of 1516 firms (Table 1.2).

This survey also classifies workers according to production (P), non-production (NP) and R&D occupational categories, which permits to investigate whether the increase in the relative demand of skilled labor came primarily from reallocations from production to non-production and R&D activities. Table 2 reports the skill intensity of each of these

¹² The survey classifies workers according to education but although it distinguishes between engineers, other college and tertiary degrees it does not distinguish within the categories of high school graduates and primary school graduates. These last two categories are pooled together for non-production and R&D workers and are divided into “skilled and specialized” and “unskilled” for production workers. As all the analysis in this paper is performed pooling high school and primary school workers into the unskilled labor category this does not present inconveniences, except that it affects the weighting of these types of workers to convert them in primary school equivalents. For this purpose workers have been assigned into one of these categories by assuming that the overall share of high school and primary school workers is the same as the one reported in the next wave of this survey (1998-2001) that does differentiate between these educational categories. Then, workers reported as high school or primary school workers in non-production and R&D are assigned in a fraction 0.46 to high school graduates. For production workers, “skilled and specialized” workers are also assigned in a fraction 0.46 to high school graduates while “unskilled” workers are assigned to primary school graduates. Alternative assignments or measures of the relative employment of skilled workers unweighted by skill premiums give similar results to the ones reported.

¹³ Estimated by mincerian equations from Household Survey data in Galeani and Sanguinetti (2003) and Gasparini et al. (2002).

activities: non-production is around 3 times more skill-intensive than production, and R&D around 15 times more skill-intensive than production. This pattern is consistent with the findings in Berman, Bound and Griliches (1994) for the U.S. regarding the higher educational level of non-production relative to production workers. Most empirical studies with industry data use production workers as a proxy for unskilled labor, and non-production workers as a proxy for skilled labor, given that the P/NP classification is the only one available in standard industry surveys and censuses. These studies capture primarily the reallocations from production to non-production labor, but miss skill upgrading within occupational categories, as I show in the next section.

Table 2
Relative Employment of Skilled Labor by Occupational Category

	1992	1996	Absolute change	Percent change
Skilled /Unskilled				
Total	0.13	0.16	0.02	0.17
Production	0.09	0.10	0.01	0.15
Nonproduction	0.26	0.31	0.04	0.15
R&D	1.33	1.49	0.16	0.12

Note: The source of the data is ETIA balanced panel of 1516 firms. Educational categories are weighted by 1992 wage premiums from Galeani and Sanguinetti (2003) and Gasparini et al (2002).

1.3.2 Spending on Technology

The survey contains information on several dimensions of spending on technology upgrading. Firms upgrade technology by performing various innovation activities like internal R&D, paying for technology transfers and buying capital goods that embody new technologies; and with different purposes like changing production processes, products, organizational forms or commercialization.

I construct a measure of spending on technology (ST) that includes these different dimensions: spending on computers and software; payments for technology transfers and

patents; and spending on equipment, materials and labor related to innovation activities performed within the firm.¹⁴

The survey contains information on ST for all years in the period 1992-1996, while information on all the rest of the variables (sales, exports, imports, employment by education, investment) is only available for the years 1992 and 1996.

1.4 Preliminary Evidence: Skill Premia and the Relative Demand for Skill

1.4.1 Skill Premia

Skill premia started growing in the 1990's after having been stable during the 1980's. Gasparini et al. (2002) report wage-premia estimates from mincerian regressions using Household Survey data. They find that the college wage premium (the wage of college graduates relative to the wage of primary school graduates) rose 19.4% between 1992 and 1998, after falling 3.7% between 1986 and 1992. The high school wage premium rose much less (4.8%), and had been constant during the previous period. Estimates for the industrial sector in Galeani et al. (2003) indicate that the college wage premium increased 7 percentage points per year during the 1990's, after being stable in the 1980's. They do not find any significant trend for the high school wage premium.

The coincidence of rising skill premia and increasing relative employment of skilled workers in the period 1992-1996 indicates that there must have been an outwards shift in the relative demand of skilled labor after trade liberalization. As the survey does not include information on wages, in the remaining of this section I analyze the increase

¹⁴ Like R&D, adaptation of new products or production processes, technical assistance for production, engineering and industrial design, organization and commercialization

in the equilibrium relative demand for skilled labor in the industrial sector, measured as the relative employment of skilled and unskilled workers.

1.4.2 Decompositions of the Change in the Relative Demand for Skilled Labor

The increase in the aggregate relative demand for skilled labor could be mainly driven by product demand reallocations towards skill-intensive sectors or activities, holding skill intensity within activities constant, or by increases in skill intensity within activities, holding product demand constant. Assessing the relative importance of these two channels is a necessary step in the investigation of the causes of the increase in the aggregate demand for skill. Product demand reallocations can be driven directly by trade or changes in demand for goods, while within activity increases in skill intensity point towards changes in technology, leading to a different assessment of the role of trade through this channel. I perform three different decompositions of the increase in the aggregate demand of skilled labor: first between and within occupational categories (P, NP and R&D); second within and between sectors; third within and between firms.

To assess the importance of skill upgrading within occupational categories relative to reallocations from production to non production and R&D, I perform the following decomposition of the change in skill intensity from 1992 to 1996:

$$\Delta\left(\frac{S}{U}\right) = \sum_c \Delta\left(\frac{U_c}{U}\right) \overline{\left(\frac{S}{U}\right)}_c + \sum_c \overline{\left(\frac{U_c}{U}\right)} \Delta\left(\frac{S}{U}\right)_c$$

where $c = P, NP, R\&D$; (U_c / U) is the share of unskilled workers employed in category c ; $(S / U)_c$ is skill intensity in category c ; a bar over a term denotes a mean over time (1992 and 1996) and a Δ before a term denotes a change over time (from 1992 to

1996). The first term on the right reports the change in aggregate skill intensity attributable to shifts in employment shares between occupational categories holding skill intensity within categories constant. The second term reports the change in aggregate skill intensity attributable to changes in skill intensity within each occupational category.

Table 3 reports the between and within decompositions of the aggregate increase in skill intensity in the period 1992-1996. Of the 17 percentage point increase, only 2 points are explained by reallocations from production to non-production and R&D occupational categories, and 15 points correspond to skill upgrading within categories, of which 7.5 points correspond to production and 6.6 points to non-production. That most skill upgrading occurs within occupational categories suggests that studies that use variation between these categories as proxies for skill upgrading might be missing an important part of it. In addition, it points towards changes in the production function within occupational categories, favoring the technological change over other explanations for skill upgrading that rely on reallocations of demand towards skill-intensive non-production activities due to outsourcing of production activities or the increasing importance of services over goods.

Table 3
Decomposition of the Variation in the Relative Employment
of Skilled Labor by Occupational Category
Percent Changes

	Production	Non Production	R&D	Total
Variation Within	0.075	0.066	0.007	0.15
Variation Between	-0.007	0.021	0.009	0.02
Total				0.17

Note: The source of the data is ETIA balanced panel of 1516 firms. Educational categories are weighted by 1992 wage premiums from Galeani and Sanguinetti (2003) and Gasparini et al (2002).

The relative importance of technological change versus product demand reallocations can also be assessed by decomposing the aggregate increase in skill intensity in changes within and across industries. If the increase in the relative demand of skilled labor comes from trade, holding technology constant, there would be no change in skill intensity within sectors, but reallocations of labor towards skill-intensive sectors. In this case the decomposition is:

$$\Delta\left(\frac{S}{U}\right) = \sum_j \Delta\left(\frac{U_j}{U}\right) \overline{\left(\frac{S}{U}\right)}_j + \sum_j \overline{\left(\frac{U_j}{U}\right)} \Delta\left(\frac{S}{U}\right)_j$$

where j = industry at 4-digit-SIC classification.

Table 4 reports the between and within industry decompositions of the aggregate increase in skill intensity in the period 1992-1996. All the 17 percentage points increase is explained by within-industry skill upgrading, the between component being small and negative. Moreover, all of it is explained by skill upgrading within firms. There is one important caveat to take into account for interpretation of this evidence: the sample I analyze does not contain entry and exit, thus the reallocations across sectors and firms that occur through entry and exit are missed in these calculations. Still, as the balanced panel represents 44% of industrial output, this evidence points towards the relative importance of skill upgrading within sectors and firms as a source of the overall increase in the relative demand of skilled labor and the skill premium.

Table 4
Decomposition of the Variation in the Relative Employment
of Skilled Labor by Sectors and Firms

Percent Changes

	Total	Between	Within
Industries at 2-digit-SIC	0.173	-0.001	0.175
Industries at 4-digit-SIC	0.173	-0.011	0.185
Firms	0.180	-0.025	0.204

Note: The source of the data is ETIA balanced panel of 1516 firms. Educational categories are weighted by 1992 wage premiums from Galeani and Sanguinetti (2003) and Gasparini et al (2002). Firm decompositions exclude 7 firms with zero unskilled workers

That most skill upgrading occurred within 4-digit-SIC industries is consistent with the findings in Berman, Bound and Griliches (1994) for the U.S. and the difficulties for identifying a significant effect of trade on the skill premium through variation across sectors in Argentina (Galeani and Sanguinetti (2003)) and Colombia (Attanasio et al. (2002)). This evidence points towards technology upgrading within sectors and firms as the main cause of the increase in the relative demand of skilled labor. Thus, the next sections focus on investigating the effects of trade on technology adoption, and its effects on skill upgrading through that particular channel.

5 Theoretical Framework

The decompositions of the increase in the relative demand of skilled labor reported in last section point towards technology upgrading within sectors and firms being the main cause of the increase in the aggregate relative demand of skilled labor. This section develops a simple model to illustrate the links between trade, capital account liberalization and technology adoption, focusing on within-sector firm heterogeneity rather than differences in skill intensity across sectors.

The setup of the model incorporates increasing returns to scale and monopolistic competition as in Krugman (1979, 1980); heterogeneous firms as in Melitz (2003); and endogenous technology choice as in Yeaple (2005). The main purpose of the model is to illustrate the effects of trade and capital account liberalization on the exporting and technology adoption decisions of firms, focusing in particular on how differences in initial productivity determine heterogeneous responses for continuing exporters, new exporters and never exporters, providing thus a basis for the empirical identification of the effects of trade on technology adoption and skill upgrading.

The model is partial equilibrium in the sense that it describes a single industry that is assumed small enough not to affect equilibrium wages. The exposition starts by describing the setup of the model and analyzing the profit maximizing exporting and technology choice of firms with different productivity levels. I then derive comparative static implications for reductions in exporting costs and in the cost of adopting new technologies, and finally relate these predictions to the observable variables in the data.

The analysis is limited in the following ways: first, I assume that the home country is small enough not to affect the price index in the foreign country; second, I abstract from entry and exit, as the model only intends to describe the within firm effects of trade and capital account liberalization; third I do not solve for the home industry equilibrium price, abstracting from the effects of import tariff reductions on the home price, and the effects of technology upgrading of domestic firms.

5.1 Setup of the Model

Demand

There is a representative consumer with CES preferences over a continuum of varieties of good q .

$$U = \left[\int_0^N q(i)^\rho di \right]^{\frac{1}{\rho}}, \quad 0 < \rho < 1$$

Consumers maximize utility subject to the budget constraint

$$\int_0^N p(i)q(i)di = E$$

Demand for a particular variety i is: $q(i) = \frac{E}{P} \left(\frac{p(i)}{P} \right)^{-\sigma}$

where $\sigma = 1/(1-\rho) > 1$ is the constant elasticity of substitution and $P = \left[\int_0^N p(i)^{1-\sigma} di \right]^{\frac{1}{1-\sigma}}$.

Supply

The supply side is characterized by monopolistic competition. Each variety is produced by a single firm, and there is free entry into the industry. As in Yeaple (2005) firms can choose to produce with two different technologies H and L that feature a constant marginal cost (c) and a fixed cost (f). Acquisition of technology H requires a higher fixed cost in terms of payments for technology adoption and capital goods that embody new technologies ($f_H > f_L$), but guarantees a lower marginal cost ($c_H < c_L$). Marginal costs are constant and reflect wage payments to two types of labor: skilled (S) and unskilled (U), employed in fixed proportions. Technology H is more skill-intensive than technology L .

As in Melitz (2003) firms are heterogeneous in their productivity, in the sense that marginal labor cost varies across firms utilizing the same technology. This idiosyncratic component of labor productivity is indexed by φ . More productive firms need to hire fewer workers to attain the same level of output, holding technology constant.

The total cost function for technology T is:

$$TC_T(\varphi) = f_T + c_T \frac{q}{\varphi} \quad T = H, L$$

where:

$$c_L = a_{LU} + \frac{w_S}{w_u} a_{LS}$$

$$c_H = a_{HU} + \frac{w_S}{w_u} a_{HS}$$

$$\frac{a_{HS}}{a_{HU}} > \frac{a_{LS}}{a_{LU}}$$

5.2 Firm Profit Maximization: Technology Adoption and Export Decisions

Profits in the Domestic Market

With CES preferences, the profit maximizing price is a constant mark-up over marginal cost, then a firm with productivity φ using technology T charges the following price in

the domestic market: $p_d^T(\varphi) = \frac{1}{\rho} \frac{c_T}{\varphi}$ for $T = H, L$. Quantity sold, revenues and profits

are:

$$q_d^T(\varphi) = EP^{\sigma-1} \left(\rho \frac{\varphi}{c_T} \right)^\sigma$$

$$r_d^T(\varphi) = p_d^T(\varphi) q_d^T(\varphi) = E \left(P \rho \frac{\varphi}{c_T} \right)^{\sigma-1}$$

$$\pi_d^T(\varphi) = \frac{1}{\sigma} r_d^T(\varphi) - f_T$$

Profits in the Export Market

As in Melitz (2003) there are two types of trade frictions: a per-unit iceberg cost, so that τ units need to be shipped per unit sold abroad and an initial fixed cost f_x to start exporting.

Exporting profits are:

$$\pi_*^T(\varphi) = \tau^{1-\sigma} E^*(P^* \rho)^{\sigma-1} \frac{1}{\sigma} c_H^{1-\sigma} \varphi^{\sigma-1} - f_x$$

where E^* and P^* are spending on good q and the price index in the foreign country, and f_x is the amortized per-period portion of the initial exporting cost.

Technology Adoption and Exporting decisions

Each firm has four options:

1. Use technology L and serve only the domestic market
2. Use technology L and export
3. Use technology H and serve only the domestic market
4. Use technology H and export.

The associated profit levels are:

$$\pi_d^L(\varphi) = E(P\rho)^{\sigma-1} \frac{1}{\sigma} c_L^{1-\sigma} \varphi^{\sigma-1} - f_L$$

$$\pi_x^L(\varphi) = \left[\tau^{1-\sigma} E^*(P^* \rho)^{\sigma-1} + E(P\rho)^{\sigma-1} \right] \frac{1}{\sigma} c_L^{1-\sigma} \varphi^{\sigma-1} - f_L - f_x$$

$$\pi_d^H(\varphi) = E(P\rho)^{\sigma-1} \frac{1}{\sigma} c_H^{1-\sigma} \varphi^{\sigma-1} - f_H$$

$$\pi_x^H(\varphi) = \left[\tau^{1-\sigma} E^*(P^* \rho)^{\sigma-1} + E(P\rho)^{\sigma-1} \right] \frac{1}{\sigma} c_H^{1-\sigma} \varphi^{\sigma-1} - f_H - f_x$$

To solve for the profit maximizing exporting and technology choice for each productivity level, I decompose the profit functions into four components:

1. Profits from serving the domestic market using the low technology: $\pi_d^L(\varphi)$.

2. The increase in revenues from exporting using the low technology:

$$dr_{dx}^L(\varphi) = \tau^{1-\sigma} E^*(P^* \rho)^{\sigma-1} \frac{1}{\sigma} c_L^{1-\sigma} \varphi^{\sigma-1}$$

3. The increase in revenues from domestic sales when switching to the high technology:

$$dr_d^{LH}(\varphi) = E(P\rho)^{\sigma-1} \frac{1}{\sigma} (c_H^{1-\sigma} - c_L^{1-\sigma}) \varphi^{\sigma-1}$$

4. The increase in revenues from exporting sales when switching to the high technology:

$$dr_x^{LH}(\varphi) = \tau^{1-\sigma} E^*(P^* \rho)^{\sigma-1} \frac{1}{\sigma} (c_H^{1-\sigma} - c_L^{1-\sigma}) \varphi^{\sigma-1}$$

The profit functions can then be written in terms of these four components:

$$\pi_d^L(\varphi) = \pi_d^L(\varphi)$$

$$\pi_x^L(\varphi) = \pi_d^L(\varphi) + dr_{dx}^L(\varphi) - f_x$$

$$\pi_d^H(\varphi) = \pi_d^L(\varphi) + dr_d^{LH}(\varphi) - (f_H - f_L)$$

$$\pi_x^H(\varphi) = \pi_d^L(\varphi) + dr_{dx}^L(\varphi) + dr_d^{LH}(\varphi) + dr_x^{LH}(\varphi) - f_x - (f_H - f_L)$$

Proposition 1: If a firm finds exporting profitable under technology L, then that firm also finds exporting profitable under technology H:

$$\pi_x^L(\varphi) > \pi_d^L(\varphi) \Rightarrow \pi_x^H(\varphi) > \pi_d^H(\varphi).$$

This is true because high-tech firms sell at a lower price, and thus have higher revenues from exporting than low-tech firms:

$$\pi_x^L(\varphi) > \pi_d^L(\varphi) \Rightarrow dr_{dx}^L(\varphi) - f_x > 0$$

$$\pi_x^H(\varphi) - \pi_d^H(\varphi) = dr_{dx}^L(\varphi) + dr_x^{LH}(\varphi) - f_x > dr_{dx}^L(\varphi) - f_x > 0$$

From comparison of $\pi_x^L(\varphi)$ and $\pi_d^L(\varphi)$ one can define the cutoff productivity

level φ_{dx}^L :

$$\pi_x^L(\varphi) > \pi_d^L(\varphi) \Leftrightarrow \varphi > \varphi_{dx}^L = \left[\tau^{\sigma-1} \frac{1}{E^*} (P^* \rho)^{1-\sigma} \sigma c_L^{\sigma-1} f_x \right]^{\frac{1}{\sigma-1}}$$

Proposition 1 implies that all firms with $\varphi > \varphi_{dx}^L$ export, regardless of technology choice.

Proposition 2: If a firm does not find technology H profitable when exporting, that firm does not find technology H profitable when only serving the domestic market:

$$\pi_x^L(\varphi) > \pi_x^H(\varphi) \Rightarrow \pi_d^L(\varphi) > \pi_d^H(\varphi)$$

This is true because, when a firm is exporting, the reduction in marginal costs derived from adoption of technology H increases both revenues from domestic sales and from exporting while it only increases domestic revenues if the firm is only serving the domestic market:

$$\begin{aligned} \pi_x^L(\varphi) > \pi_x^H(\varphi) &\Rightarrow dr_d^{LH}(\varphi) + dr_x^{LH}(\varphi) - (f_H - f_L) < 0 \Rightarrow \\ \pi_d^H(\varphi) - \pi_d^L(\varphi) &= dr_d^{LH}(\varphi) - (f_H - f_L) < 0 \end{aligned}$$

From comparison of $\pi_x^H(\varphi)$ and $\pi_x^L(\varphi)$ one can define the cutoff productivity

level φ_x^{LH} :

$$\pi_x^H(\varphi) > \pi_x^L(\varphi) \Leftrightarrow \varphi > \varphi_x^{LH} = \left\{ \frac{\sigma(f_H - f_L)}{\left[\tau^{1-\sigma} E^* (P^* \rho)^{\sigma-1} + E(P\rho)^{\sigma-1} (c_H^{1-\sigma} - c_L^{1-\sigma}) \right]} \right\}^{\frac{1}{\sigma-1}}$$

Proposition 2 implies that all firms with $\varphi < \varphi_x^{LH}$ use technology L, regardless of exporting status.

Finally the least productive firms do not find it profitable to adopt any of the two technologies and I assume they exit. As long as f_L is small enough relative to f_x and f_H , the minimum productivity observed is φ_d^L defined by

$$\pi_d^L(\varphi) > 0 \Leftrightarrow \varphi > \varphi_d^L = \left[\frac{1}{E} (P\rho)^{1-\sigma} \sigma c_L^{\sigma-1} f_L \right]^{\frac{1}{\sigma-1}}$$

Exporting and Technology Adoption Thresholds

There are two possible configurations for the technology and exporting status decisions:

$\varphi_{dx}^L < \varphi_x^{LH}$ and $\varphi_x^{LH} < \varphi_{dx}^L$. In the first case:

- Firms with $\varphi_d^L < \varphi < \varphi_{dx}^L$ only serve the domestic market and use the low technology.

- Firms with $\varphi_{dx}^L < \varphi < \varphi_x^{LH}$ export and use the low technology.

- Firms with $\varphi_x^{LH} < \varphi$ export and use the high technology.

In this case there are no firms using the high technology and serving only the domestic market.

In the second case ($\varphi_x^{LH} < \varphi_{dx}^L$) all exporters use the high technology. The technology and exporting choices in this case are analyzed in Appendix A. I do not focus on this case here as I observe exporters that use the low technology both in 1992 and 1996 in the data.

The condition for $\varphi_{dx}^L < \varphi_x^{LH}$ is:

$$\varphi_{dx}^L < \varphi_x^{LH} \Leftrightarrow \left[1 + \tau^{\sigma-1} \frac{E}{E^*} \left(\frac{P}{P^*} \right)^{\sigma-1} \right] \left[\left(\frac{c_L}{c_H} \right)^{\sigma-1} - 1 \right] < \frac{(f_H - f_L)}{f_x}$$

The fixed cost of technology adoption must be big enough relative to the fixed exporting cost for there to be exporters using the low technology.

As in the next subsection I only analyze the case where $\varphi_{dx}^L < \varphi_x^{LH}$, I rename those productivity thresholds to simplify notation:

- The productivity threshold for exporting to be profitable for firms using the low technology (φ_{dx}^L) is φ_x .

- The productivity threshold for adoption of technology H to be profitable for exporters (φ_x^{LH}) is φ_H .

5.3 Trade and Capital Account Liberalization

This section describes the effects of trade and capital account liberalization on the exporting and technology adoption decisions. In particular, I analyze the effects of a reduction in exporting and technology adoption costs on the productivity thresholds φ_x and φ_H .

Reduction in exporting costs

A reduction in exporting costs can occur because the variable exporting cost (τ) or the fixed exporting cost (f_x) has fallen. I concentrate on the case where variable exporting costs fall, as there is direct evidence that trade liberalization reduced variable export costs, not fixed export costs. The predictions are very similar in the case where the fixed costs fall.

A reduction in τ increases exporting revenues, thus more firms find it profitable to pay the fixed costs of entering the export market and more exporters find it profitable to pay the fixed cost of adoption of technology H .

Proposition 3: A reduction in variable export costs (τ) induces more firms to enter the export market.

This can be seen in a reduction of the cutoff φ_x :

$$\frac{\partial \varphi_x}{\partial \tau} = \left[\frac{1}{E^*} (P^* \rho)^{1-\sigma} \sigma c_L^{\sigma-1} f_x \right]^{\frac{1}{\sigma-1}} > 0$$

Proposition 4: A reduction in variable export costs (τ) induces more exporters to adopt technology H .

This results from a reduction in the cutoff φ_H :

$$\frac{\partial \varphi_H}{\partial \tau} = \left[\frac{\sigma(f_H - f_L)}{c_H^{1-\sigma} - c_L^{1-\sigma}} \right]^{\frac{1}{\sigma-1}} \left\{ \left[\tau^{1-\sigma} E^* (P^* \rho)^{\sigma-1} + E(P\rho)^{\sigma-1} \right]^{\frac{\sigma}{\sigma-1}} \tau^{-\sigma} E^* (P^* \rho)^{\sigma-1} \right\} > 0$$

Reduction in the cost of adopting new technologies

The cost of adopting technology H , if this technology is designed in developed countries and thus must be imported, is affected by import tariffs on capital goods that embody new technologies and taxes on payments for international technology transfers (τ_H). In addition, if investment in new technologies must be made one period before collecting revenues, part of the cost of adoption is given by the interest rate (R). Thus, if F_H is the cost of technology H in terms of capital goods and payments for technology transfers, the cost of adoption is $f_H = (1 + R)\tau_H F_H$. Then a reduction of tariffs on imported capital goods and taxes on technology transfers (τ_H) reduces the cost of adoption. In addition, capital account liberalization in a capital scarce country reduces the interest rate, further reducing the cost of adoption.

Proposition 5: A reduction in f_H induces more exporters to adopt technology H .

This results from a reduction in the cutoff φ_H :

$$\frac{\partial \varphi_H}{\partial f_H} = \frac{\frac{\sigma}{\sigma-1} [\sigma(f_H - f_L)]^{\frac{\sigma}{1-\sigma}}}{\left\{ \tau^{1-\sigma} E^* (P^* \rho)^{\sigma-1} + E(P\rho)^{\sigma-1} \left[c_H^{1-\sigma} - c_L^{1-\sigma} \right] \right\}^{\frac{1}{\sigma-1}}} > 0$$

The effects of liberalization on within firm exporting and technology adoption decisions

The precise predictions of the model in terms of the effects of trade and capital account liberalization on the technology adoption decisions of never exporters, new exporters and continuing exporters depend on the ordering of thresholds before and after liberalization. Next I analyze all the possible ordering of thresholds to identify which one is consistent with the broad patterns in the data, and then derive the predictions of the model for that case.

There are three possible ordering of thresholds before ($t = 0$) and after ($t = 1$) trade and capital account liberalization:

$$1. \varphi_d < \varphi_x^1 < \varphi_H^1 < \varphi_x^0 < \varphi_H^0.$$

In this case firms with:

- $\varphi_d < \varphi < \varphi_x^1$: remain serving only the domestic market and using technology L .

- $\varphi_x^1 < \varphi < \varphi_H^1$: start exporting and remain using technology L .

- $\varphi_H^1 < \varphi < \varphi_x^0$: start exporting and switch to technology H .

- $\varphi_x^0 < \varphi < \varphi_H^0$: continue exporting and switch to technology H .

- $\varphi_H^0 < \varphi$: continue exporting and using technology H .

$$2. \varphi_d < \varphi_x^1 < \varphi_x^0 < \varphi_H^1 < \varphi_H^0$$

In this case all new exporters remain using technology L . In the next section of the paper I show that this case is not consistent with what I observe in the data, as some new exporters adopt technology H .

$$3. \varphi_d < \varphi_H^1 < \varphi_x^1 < \varphi_x^0 < \varphi_H^0$$

In this case there would be no new exporters using technology L after liberalization, but I do observe new exporters using the low technology, thus this case is not consistent with the data either.

The condition to obtain case 1 is that the reduction in the cost of adopting technology H and in the variable exporting cost are big:

$$\varphi_x^1 < \varphi_H^1 < \varphi_x^0 < \varphi_H^0 \Leftrightarrow \left[1 + (\tau^1)^{\sigma-1} \frac{E}{E^*} \left(\frac{P}{P^*} \right)^{\sigma-1} \right] \left[\left(\frac{c_L}{c_H} \right)^{\sigma-1} - 1 \right] < \frac{(f_H^1 - f_L)}{f_x} < \left[1 + (\tau^0)^{\sigma-1} \frac{E}{E^*} \left(\frac{P}{P^*} \right)^{\sigma-1} \right] \left[\left(\frac{c_L}{c_H} \right)^{\sigma-1} - 1 \right] < \frac{(f_H^0 - f_L)}{f_x}$$

5.4 Model Predictions on Technology Spending and Skill Upgrading

1. The level of spending on technology after liberalization is f_L for firms in the range $\varphi < \varphi_H^1$: never exporters and the least productive new exporters; f_H for firms in the range $\varphi_H^1 < \varphi$: the most productive new exporters and all continuing exporters.
2. The change in spending on technology after liberalization is: zero for firms in the range $\varphi < \varphi_H^1$: never exporters and the least productive new exporters; $f_H - f_L$ for firms in the range $\varphi_H^1 < \varphi < \varphi_H^0$: the most productive new exporters and the least productive continuing exporters; zero for firms in the range $\varphi_H^0 < \varphi$: the most productive continuing exporters.

3. The level of skill intensity before liberalization is: $\frac{a_{LS}}{a_{LU}}$ for firms in the range $\varphi < \varphi_H^0$: non exporters, new exporters and the least productive continuing exporters; $\frac{a_{HS}}{a_{HU}}$ for firms in the range $\varphi_H^0 < \varphi$: the most productive continuing exporters.
4. The change in skill intensity is: zero for firms in the range $\varphi < \varphi_H^1$: non exporters and the least productive new exporters; $\frac{a_{HS}}{a_{HU}} - \frac{a_{LS}}{a_{LU}}$ for firms in the range $\varphi_H^1 < \varphi < \varphi_H^0$: the most productive new exporters and the least productive continuing exporters; zero for firms in the range $\varphi_H^0 < \varphi$: the most productive continuing exporters.
5. Skill upgrading is caused by technology upgrading, then firms that upgrade technology also increase their skill intensity.

6 Empirics

In this section I try to identify the effects of trade and capital account liberalization on technology adoption and skill upgrading within firms. As liberalization affects all firms and sectors in the economy, the identification strategy is based on the heterogeneous responses of firms of different initial productivity levels, as predicted by the model presented in the previous section.

First I describe broad patterns in the data and relate them to the claim in the theoretical section that there was only one ordering of cutoffs consistent with these patterns. Second, I report evidence on financing constraints that implies that the optimal

technology choices predicted in the previous section are unattainable for small and domestically-owned firms, suggesting a role for FDI both as a control and as an additional measure of the effects of capital account liberalization on skill and technology upgrading. Finally, I discuss the empirical strategy and conduct empirical tests of the 5 predictions derived from the model.

6.1 Broad Patterns in the Data: Exporter Premia

According to the model in the previous section, there should be systematic differences in productivity, size, spending on technology and skill intensity, between continuing exporters, new exporters and non exporters.

In the model heterogeneity is given by labor productivity holding technology constant (φ), which is not observable in the data. As a proxy for productivity (φ) I use initial labor productivity defined as sales divided by employment in primary school equivalents in 1992 ($Ptiv$).¹⁵ This proxy also incorporates initial differences in choice variables like capital stock per worker and technology, which I do not observe in the data, but these are expected to be positively correlated with idiosyncratic productivity differences (φ), so that the ordering of firms is preserved by the proxy. As measures for firm size I use employment, employment in primary school equivalents and sales. Skill

¹⁵ Value added would be a better measure than sales, but it is not available in the data. As differences in productivity are always computed relative to the 4-digit-SIC industry average, if firms within each industry have a similar value added over sales ratio, the order of productivity would be similar using sales or value added in the productivity measure. Employment in primary school equivalents is computed as: $L_t = S_t (w_s / w_u)_{1992} + U_t$ where $t=1992, 1996$. Labor productivity is computed as sales divided by employment in primary school equivalents rather than employment per worker as it intends to be a proxy for the idiosyncratic component of labor productivity (φ) and thus should not include differences in productivity due to differences in skill.

intensity is measured as the share of skilled labor in employment in primary school equivalents:

$$\left(\frac{L_s}{L}\right)_t = \frac{S_t (w_s / w_u)_{1992}}{S_t (w_s / w_u)_{1992} + U_t}$$

where $t = 1992, 1996$. As skilled labor is weighted by the skill premium in 1992, changes in this share only reflect changes in quantities of skilled and unskilled labor, and not changes in the skill premium.

Table 5 reports the differences between firms that exported both in 1992 and 1996 (continuing exporters), firms that exported in 1996 but not in 1992 (new exporters), and firms that only serve the domestic market (non exporters). The continuing exporter and new exporter premia are estimated from a regression of the form

$$\ln Y_{ij} = \alpha + \alpha_{NE} NE_{ij} + \alpha_{EE} EE_{ij} + \alpha_{EN} EN_{ij} + I_j + \varepsilon_{ij}$$

where i indexes firms, j indexes industries (4-digit-SIC classification); NE are new exporters, EE are continuing exporters, EN are firms that exported in 1992 but didn't in 1996,¹⁶ and the reference category relative to which differences are estimated is non-exporters; I_j are industry dummies, and Y is the firm characteristic for which the premia are estimated. Firm characteristics include labor productivity, size, the share of skilled labor; and spending on technology per worker.

Exporter premia in size and productivity are positive and significant at 1% both in 1992 and 1996, and bigger for continuing exporters than for new exporters. This pattern is consistent with the model, as continuing exporters are more productive thus bigger than

¹⁶ Only 28 out of 1516 firms are in this category, thus it is hard to interpret the coefficients on this group, specially because some of the zeros for 1996 could be imputed. I only include them as a control group.

new exporters, which in turn are more productive than non-exporters, both initially and after liberalization.

In the theoretical section I mentioned that there was only one ordering of cutoffs prior to liberalization that was consistent with the data ($\varphi_{dx}^L < \varphi_x^{LH}$). In that ordering, only continuing exporters were using the high technology before liberalization. This is the only case consistent with the following patterns in exporter premia: first, spending on technology per worker is 37% higher for continuing exporters in 1992 and their share of skilled labor is 6.5 percentage points higher than that of non exporters (41% higher than the overall average share of skilled labor); second, firms that would start exporting after 1992 do not invest more in technology that year, and their skill intensity is only 1.9 percentage points higher than that of non exporters, the difference being significant only at 10% level.

Additionally, I mentioned that there was only one ordering of cutoffs before and after liberalization that was consistent with the data: $\varphi_d < \varphi_x^1 < \varphi_H^1 < \varphi_x^0 < \varphi_H^0$. In this case, only the most productive new exporters would update technology, which is consistent with average skill intensity and spending on technology for new exporters being higher than for non-exporters, but lower than for continuing exporters in 1996. Also, the least productive continuing exporters would update technology, which is consistent with the share of skilled labor and spending on technology increasing in 1996 for always exporters.¹⁷

¹⁷ There were two other possible orderings of cutoffs. In the second one, all new exporters would remain using technology L after liberalization, which is not consistent with the share of skilled labor and spending on technology per worker being higher for new exporters than for non-exporters in 1996; In the third one, all new exporters would use technology H after liberalization, which is not consistent with spending on technology per worker the average share of skilled labor being lower for new exporters than for continuing exporters.

Table 5
Exporter Premia

	1992			1996		
	Continuing Exporters	New Exporters	Observ.	Continuing Exporters	New Exporters	Observ.
Employment	1.481 [0.071]***	0.851 [0.083]***	1516	1.491 [0.070]***	1.017 [0.080]***	1516
Empl. in prim. school equiv.	1.521 [0.072]***	0.862 [0.084]***	1516	1.538 [0.071]***	1.035 [0.081]***	1516
Sales	1.817 [0.086]***	1.058 [0.099]***	1516	1.997 [0.091]***	1.305 [0.104]***	1516
Labor Productivity	0.296 [0.047]***	0.196 [0.055]***	1516	0.459 [0.048]***	0.270 [0.055]***	1516
Share of skilled labor	6.478 [1.103]***	1.869 [1.073]*	1516	7.693 [1.122]***	3.134 [1.124]***	1516
Spending in Technology per worker	0.370 [0.141]***	0.200 [0.164]	994	0.580 [0.121]***	0.409 [0.141]***	1128

Note: Robust standard errors in brackets. * indicates significant at 10%; ** significant at 5%; *** significant at 1%
Observations in each category are described below.

	Observations
New Exporters	251
Continuing Exporters	585
Stopped Exporting	28
Non Exporters	652
Total	1516

6.2 Broad Patterns in the Data: Evidence on Financial Underdevelopment

The survey also contains information on the sources of financing technology spending that can be used to qualify and extend the predictions of the model regarding optimal technology choice. Access to credit is particularly important in the presence of fixed costs of technology adoption, as the finance needs of firms would be high relative to their cash flow in this case. If firms are credit constrained in the sense that there is a collateral requirement to receive a loan, bigger firms would benefit more from the reduction in the cost of adopting new technologies, as bigger firms are more likely to be above the collateral threshold required to finance the fixed costs of technology adoption, or can finance it with current profits. Foreign-owned firms would also be at an advantage as they can obtain funds from their parent firms in developed capital markets.

Table 6.1 reports the sources of financing technology spending. On average, firms finance 60% of their spending with own funds, which suggests that financial markets are underdeveloped.

Table 6.2 reports the coefficients of a regression of the form:

$$Y_{ij} = \alpha + \alpha_{NE}NE_{ij} + \alpha_{EE}EE_{ij} + \alpha_{EN}EN_{ij} + \alpha_{FO}FO_{ij} + \beta \log L_{ij} + \gamma \log Ptiv_{ij} + I_j + \varepsilon_{ij}$$

where i indexes firms, j indexes 4-digit-SIC industries; FO is an indicator variable for foreign ownership, L is a measure of firm size given by employment in primary school equivalents; $Ptiv$ is labor productivity; I_j are industry dummies and Y is the share of technology spending financed by each particular source. Size has a positive and significant effect on the share financed by private banks, as predicted by standard credit constraint models. Additionally, foreign-owned firms finance 13% more of their spending

with funds from the parent firm, and 12% less with own funds, which is consistent with them being less affected by the lack of development of local financial markets than domestically-owned firms.

This evidence on financial underdevelopment suggests that there might be a differential effect of trade and capital account liberalization on technology and skill upgrading for foreign-owned firms, as they would have better access to funds to finance technology upgrading. In addition, as capital account liberalization included the deregulation of FDI, this evidence suggests an additional effect of capital account liberalization on technology and skill upgrading, through increased FDI that would allow otherwise credit constrained firms to choose technology optimally.

Finally, it is interesting to note that new exporters finance 13% less of their spending with own funds, which is consistent with them being the group of firms adopting the new technology, as predicted by the model in the last section.

Table 6.1
Sources of Financing Innovation Spending: Averages across All Firms

Average share of innovation spending financed by:

	Own Funds	Official Banks	Private Banks	Foreign Financing	Gov. Programs	Parental Firm	Clients	Providers	Other
Average	60.588 [1.297]	5.846 [0.564]	17.303 [0.894]	3.915 [0.467]	0.589 [0.190]	4.014 [0.564]	0.776 [0.177]	5.864 [0.503]	1.104 [0.221]
Observations	950	950	950	950	950	950	950	950	950

Note: Robust standard errors in brackets

Table 6.2
Sources of Financing Innovation Spending: Differences

LHS variable: share of innovation spending financed by:

	Own Funds	Official Banks	Private Banks	Foreign Financing	Gov. Programs	Parental Firm	Clients	Providers	Other
New Exporters	-13.160 [4.093]***	2.664 [2.034]	4.711 [2.834]*	2.781 [1.650]*	0.768 [0.709]	0.876 [1.627]	-1.196 [0.605]**	2.242 [1.859]	0.315 [0.730]
Continuing Exporters	-2.944 [3.676]	0.492 [1.457]	3.609 [2.591]	2.637 [1.300]**	-0.583 [0.351]*	-0.403 [1.405]	-0.680 [0.413]	-1.553 [1.516]	-0.576 [0.675]
Stopped Exporting	-9.351 [8.998]	-0.001 [6.034]	9.721 [6.879]	0.267 [1.945]	-1.532 [1.061]	-1.014 [1.944]	-0.717 [0.927]	2.709 [7.517]	-0.081 [0.945]
Foreign Owned	-12.572 [3.980]***	-1.100 [1.412]	1.295 [2.673]	-0.638 [1.435]	0.096 [0.708]	13.277 [2.414]***	0.432 [0.477]	-1.050 [1.181]	0.260 [0.605]
Log(Employment ₁₉₉₂)	-1.835 [1.332]	-1.329 [0.686]*	2.548 [0.832]***	0.622 [0.541]	0.032 [0.150]	0.057 [0.465]	-0.319 [0.191]*	0.406 [0.464]	-0.183 [0.188]
Log(Productivity ₁₉₉₂)	-1.528 [2.096]	-0.897 [0.936]	0.939 [1.500]	1.815 [0.784]**	-0.052 [0.296]	0.725 [0.838]	-0.359 [0.334]	-0.527 [0.787]	-0.117 [0.330]
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	950	950	950	950	950	950	950	950	950
R-squared	0.19	0.15	0.14	0.14	0.11	0.22	0.16	0.11	0.10

Note: Robust standard errors in brackets. * indicates significant at 10%; ** significant at 5%; *** significant at 1%

6.3 Econometric Strategy

When taking the model predictions to the data, I test for within sector discrete differences between new exporters, continuing exporters, foreign owned firms and domestically-owned non exporters, both in levels and changes in technology spending and skill intensity. In this section I test the following five theoretical predictions:

1. The level of technology spending after liberalization is discretely higher for firms in the upper range of the productivity distribution: the most productive new exporters and all continuing exporters.
2. The change in technology spending after liberalization has an inverted U shape, being discretely higher for firms in the middle range of the productivity distribution, as those are switching to technology H: the most productive new exporters and the least productive continuing exporters.
3. The level of skill intensity before liberalization is discretely higher for firms that had already adopted technology H: the most productive continuing exporters.
4. The change in skill intensity after liberalization has an inverted U shape, being discretely higher for firms in the middle range of the productivity distribution: the most productive new exporters and the least productive continuing exporters.
5. Skill upgrading is caused by technology upgrading, then firms that upgrade technology faster also upgrade skill faster.

Prediction 1: Level of Spending on Technology in the Period 1993-1996

I estimate differences in the level of technology spending through the following regression:

$$\begin{aligned} \log(ST)_{ij} = & \alpha + \alpha_{NE}NE_{ij} + \alpha_{EE}EE_{ij} + \alpha_{EN}EN_{ij} + \alpha_{FO}FO_{ij} \\ & + \beta_1 \log L_{ij} + \beta_2 (\log L_{ij})^2 + \beta_3 (\log L_{ij})^3 + \gamma \log Ptiv_{ij} + I_j + \varepsilon_{ij} \end{aligned} \quad (1)$$

The LHS variable is spending on technology (ST) in the period after trade liberalization (1993-1996), that would be a measure for the per-period portion of spending required to maintain or adopt a given technology (f_H, f_L).

The measure of technology spending includes several dimensions, some of which can be thought of as a variable cost (spending on personal computers), and some that have the characteristics of a fixed cost (spending on computerized control production systems, patents). The presence of fixed costs of technology adoption implies that firms using the high technology have a discrete increase in technology spending. In the model, technology spending after liberalization is f_L for firms in the range $\varphi < \varphi_H^1$, and f_H for firms in the range $\varphi_H^1 < \varphi$, then the relationship between technology spending and initial productivity is discontinuous. Initial productivity would still have a positive linear effect on technology spending if part of it was a variable cost.

Then, I try to identify the differences in technology choice across firms by looking for discrete differences in technology spending for the firms that are predicted to use technology H in the model: new exporters and continuing exporters. As these are bigger and more productive than non-exporters, I control for initial productivity and size, to make sure I am capturing the effect of exporting on the technology adoption decision,

and not the direct effects of initial heterogeneity. I also control for 4-digit-SIC industry dummies, to make sure I am capturing differences driven by heterogeneous responses of firms to trade liberalization, and not by other differences like the speed of technological change in exporting sectors.

I include size as a control, as this variable is correlated with exporting status and there are several reasons for size to have a direct effect on technology spending. First, initial productivity (φ) is also correlated with firm size, thus the long run component of productivity and past productivity shocks might be better captured by size than by current labor productivity. Second, other determinants of size would affect technology spending directly if part of it is a variable cost. Finally, the evidence on credit constraints in the last section suggests that bigger firms are more likely to be above the collateral threshold required to pay the fixed costs of technology adoption. The measure of initial firm size I use is employment in primary school equivalents in 1992 (L), so that it is complementary with the productivity measure ($Ptiv$).

Finally, another firm characteristic that is correlated with exporting status and can have a direct effect on technology adoption is foreign ownership. That foreign-owned firms finance their investment in technology with funds from their parental firm implies that they can take advantage of the fall in the cost of adoption better than credit constrained domestically-owned firms.

As 256 of the 1511 firms¹⁸ have zero spending on technology in the period 1993-1996, OLS estimation of equation (1) can only be performed in the sample of firms with

¹⁸ The analysis below is performed on a sample of 1511 firms as 4 firms in the balanced panel of 1516 firms have no information of foreign ownership.

positive ST, thus to correct for sample selection, I also estimate it using Heckman's selection model.

The selection equation is:

$$ST_{ij} = 1[\alpha + \alpha_{NE}NE_{ij} + \alpha_{EE}EE_{ij} + \alpha_{EN}EN_{ij} + \alpha_{FO}FO_{ij} + \beta_1 \log L_{ij} + \gamma \log Ptiv_{ij} + I_j + v_{ij} > 0] \quad (2)$$

Selection comes from the existence of fixed costs of technology adoption, and thus a nonlinear effect of size on technology spending. From the point of view of small firms, buying personal computers and software is a fixed technology adoption cost that they can't finance, even if they found it profitable to adopt those technologies. Thus firm size is expected to have a positive effect on the extensive margin of technology adoption. For medium-small firms that have already adopted those technologies, increases in firm size does not have an effect on technology spending, but after firms have grown enough, size has a positive effect again, as computers and software become variable costs for bigger firms.

The procedure to estimate the coefficients in equation (1) then follows two steps: first, obtaining the Probit estimates of the coefficients in the selection equation (2) using the full sample, second using those estimated coefficients to obtain the selection correction term (inverse Mills ratio) and finally estimating equation (1) plus the selection correction term. As there are no additional variables in the selection equation, the coefficients in equation (1) are identified due to the nonlinearity of the correction term.

Table 7 reports the estimated coefficients for equation (1). Column 1 reports the OLS coefficients (OLS 1) for the sample with positive spending on technology and column 2 reports the Heckman Selection Model coefficients (Heckman 1). Column 6 reports the coefficients in the selection equation (2). The results indicate that there is no

selection bias, as the hypothesis of zero correlation between ε and v can't be rejected, thus the OLS and Heckman Selection Model coefficients and their standard errors are very similar. I then describe the OLS results.

New exporters and continuing exporters spend 66% and 50% more in technology than domestically-owned non-exporters. This discrete difference in technology spending, after controlling for size and productivity, is consistent with the existence of fixed costs of technology adoption that only exporters find profitable to pay, as predicted by the model.

Foreign-owned firms spend 70% more in technology, which is consistent with the existence of fixed costs of technology adoption coupled with credit constraints, as some domestically-owned firms would find it profitable to upgrade technology but would be prevented to do so by credit constraints.

Productivity also has a positive effect on technology adoption, as expected. The effect of size is nonlinear, the results point towards a big effect of size on the extensive margin decision to spend a positive amount on technology, but its effect on the intensive margin becomes weaker for small-medium size firms and stronger for medium-big firms.

The rest of the columns report OLS and Heckman Selection Model coefficients for different degree polynomials in size, the coefficients on exporting status and foreign ownership are very similar and significant at 1% in all specifications.

Table 7

Test of Prediction 1: Levels of Technology Spending

LHS variable: Log Spending on Technology from 1993 to 1996

	1	2	3	4	5	6	7
	OLS 1	Heckman 1	OLS 2	Heckman 2	OLS 3	Selection Equation 1	Selection Equation 2
New Exporters	0.666 [0.139]***	0.726 [0.138]***	0.686 [0.141]***	0.751 [0.139]***	0.650 [0.142]***	0.755 [0.156]***	0.755 [0.156]***
Continuing Exporters	0.504 [0.139]***	0.547 [0.134]***	0.528 [0.139]***	0.574 [0.135]***	0.516 [0.139]***	0.520 [0.139]***	0.518 [0.139]***
Stopped Exporting	0.517 [0.383]	0.527 [0.365]	0.513 [0.381]	0.524 [0.364]	0.456 [0.384]	-0.001 [0.308]	-0.001 [0.309]
Foreign Owned	0.701 [0.129]***	0.696 [0.123]***	0.722 [0.129]***	0.716 [0.122]***	0.768 [0.130]***	0.101 [0.185]	0.100 [0.186]
Log(Employment ₁₉₉₂)	-1.896 [0.831]**	-1.768 [0.806]**	0.257 [0.208]	0.359 [0.217]*	1.042 [0.048]***	0.442 [0.050]***	0.444 [0.051]***
Log(Employment ₁₉₉₂) ²	0.527 [0.168]***	0.514 [0.161]***	0.080 [0.020]***	0.073 [0.020]***		0.264 [0.069]***	0.265 [0.069]***
Log(Employment ₁₉₉₂) ³	-0.029 [0.011]***	-0.029 [0.010]***				-2.307 [0.444]***	-2.317 [0.445]***
Log(Productivity ₁₉₉₂)	0.596 [0.071]***	0.615 [0.069]***	0.591 [0.070]***	0.612 [0.069]***	0.589 [0.071]***		
Constant	1.670 [1.325]	-0.114 [1.356]	-1.580 [0.598]***	-3.343 [0.745]***	-3.307 [0.355]***		
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1256	1511	1256	1511	1256	1511	1511
R-squared	0.64		0.63		0.63		
Rho						0.190 [0.122]	0.207 [0.125]
Sigma						1.433 [0.030]	1.438 [0.031]
Lambda						0.273 [0.176]	0.297 [0.181]
Wald test of indep. eqns. (Rho = 0):		chi2(1)				2.31	2.60
		Prob > chi2				0.13	0.11

Robust standard errors in brackets. * indicates significant at 10%; ** significant at 5%; *** significant at 1%

Prediction 2: Changes in Technology Spending

The model predicts that the most productive firms entering the export market upgrade technology, and only the least productive continuing exporters upgrade technology, as the most productive ones would have already adopted it before liberalization. As initial technology is not observed, I use the change in technology spending after liberalization as a measure of technology upgrade.

The resulting specification is:

$$\begin{aligned} \log ST_{ij96-93} - \log ST_{ij92} = & \alpha + \alpha_{NE} NE_{ij} + \alpha_{EE} EE_{ij} + \alpha_{EN} EN_{ij} + \alpha_{FO} FO_{ij} \\ & + \beta \log L_{ij} + \gamma \log Ptiv_{ij} + I_j + \varepsilon_{ij} \end{aligned} \quad (3)$$

The LHS variable is the change in technology spending after liberalization, that is the difference between average spending on the period 1993-1996 ($ST_{ij96-93}$) and spending on 1992 (ST_{ij92}). This specification intends to capture the change in technology, which is expected to be discretely higher for firms that switched from the low to the high technology, such as new exporters and low productivity continuing exporters.

This regression can only be run on a sub-sample of firms that have positive ST in both sub-periods, 973 out of the 1256 that had positive ST on the period 1993-1996 and the total of 1511 firms.

Table 8 reports coefficients for equation (3) estimated by OLS. New exporters are the only group for which there is a differential increase in spending on technology after trade liberalization, and this is the group that is switching from the low to the high technology in the model, the estimated difference is 43% and significant at 1%. The control for initial heterogeneity (labor productivity) is not significant because the regression is run in differences of logs, thus initial multiplicative heterogeneity is not omitted from the regression. When the controls for size and productivity are omitted, the

coefficient on continuing exporters becomes significant at 10%, and it is half the one for new exporters. This is consistent with the prediction that the least productive continuing exporters would switch to the high technology. The coefficient on foreign-owned firms also becomes significant at 5% when the controls are omitted.

Table 8
Test of Prediction 2: Changes in Technology Spending

LHS variable: $\text{Log ST}_{(1996-1993)} - \text{Log ST}_{(1992)}$		
	1	2
New Exporters	0.427 [0.123]***	0.479 [0.120]***
Continuing Exporters	0.114 [0.119]	0.212 [0.110]*
Stopped Exporting	-0.172 [0.338]	-0.112 [0.339]
Foreign Owned	0.147 [0.107]	0.215 [0.099]**
Log(Employment ₁₉₉₂)	0.097 [0.044]**	
Log(Productivity ₁₉₉₂)	-0.005 [0.062]	
Constant	-0.216 [0.332]	0.192 [0.078]**
Industry dummies	Yes	Yes
Observations	973	973
R-squared	0.16	0.16

Robust standard errors in brackets. * indicates significant at 10%; ** significant at 5%; *** significant at 1%.

Predictions 3 and 4: Levels and Changes in Skill Intensity

In this subsection I test the predictions of the model regarding the relationship between technology and skill upgrading. I first investigate the differences in initial skill intensity and skill upgrading between exporters and non-exporters, and later relate the differences in skill upgrading to technology choice.

Table 9 reports the differences in initial skill intensity and skill upgrading between exporters, foreign-owned firms and domestically-owned non-exporters. The 1992 average share of skilled labor for the whole sample is 15.7%. Continuing Exporters had a 4.3 percentage points higher skill intensity, while firms that would export in 1996 but were not exporting in 1992 had the same skill intensity as domestically-owned non-exporters (Column 1). During the period 1992-1996 average skill upgrading for the whole sample was 1.64 percentage points, but both continuing exporters and new exporters upgraded skill faster (1.12 and 1.24 percentage points, respectively) than domestically-owned firms (Column 3). These patterns are consistent with the predictions of the model, as the only firms using the skill-intensive high technology before liberalization were exporters, and expansion of exporting opportunities would lead both the least productive exporters and the most productive new exporters to upgrade technology and skill.

The finding that foreign-owned firms are initially more skill-intensive than domestically-owned firms is also consistent with them being able to finance their investment in technology at lower interest rates before and after liberalization.

Table 9
Tests of Predictions 3 and 4: Levels and Changes in Skill Intensity

	(1) LHS variable: Initial Share of Skilled Labor (92)	(2) LHS variable: Final Share of Skilled Labor (96)	(3) LHS variable: Change in the Share of Skilled Labor (96-92)
New Exporters	1.352 [1.027]	2.590 [1.075]**	1.238 [0.461]***
Continuing Exporters	4.341 [1.093]***	5.460 [1.131]***	1.119 [0.396]***
Stopped Exporting	6.202 [2.582]**	3.865 [2.482]	-2.338 [1.714]
Foreign Owned	8.888 [1.338]***	9.254 [1.377]***	0.366 [0.475]
Constant	11.988 [0.650]***	12.971 [0.664]***	0.983 [0.237]***
Industry dummies	Yes	Yes	Yes
Observations	1511	1511	1511
R-squared	0.35	0.36	0.10

Robust standard errors in brackets. * indicates significant at 10%; ** significant at 5%; *** significant at 1%.

Prediction 5: Technology and Skill Upgrading

In this subsection I investigate the relationship between technology and skill upgrading. I present two regressions. In the first one the RHS variable is the growth in technology spending per worker, and it intends to capture the change in technology, and the LHS variable is the change in the share of skilled labor:

$$\left(\frac{L_s}{L}\right)_{ij96} - \left(\frac{L_s}{L}\right)_{ij92} = \alpha + \beta \left[\log\left(\frac{ST_{93-96}}{L_{96}}\right)_{ij} - \log\left(\frac{ST_{92}}{L_{92}}\right)_{ij} \right] + I_j + e_{ij} \quad (4)$$

This regression can only be run in the sub-sample of firms that have positive spending on technology in both sub-periods (973 out of 1516 firms). Thus, as a robustness check, I also present another regression where the RHS variable is average

spending on technology in the period 1993-1996 (ST), that would be a measure for the per period spending required to maintain or adopt a given technology (f_H, f_L). In that case, the initial share of skilled labor is included in the regression as it is expected to be correlated with the initial level of technology, in an attempt to capture the effects of technology upgrading on skill upgrading. The equation for the second regression is:

$$\left(\frac{L_s}{L}\right)_{ij96} - \left(\frac{L_s}{L}\right)_{ij92} = \alpha + \beta \log\left(\frac{ST_{93-96}}{L_{92}}\right)_{ij} + \gamma \left(\frac{L_s}{L}\right)_{ij92} + I_j + v_{ij} \quad (5)$$

Table 10.1 reports OLS estimation of the coefficients on equation (4). The coefficient on the change in spending on technology per worker is significant at 1% and has practically the same magnitude when initial skill is included in the regression, indicating that the change in spending on technology per worker is a good measure of technology upgrading. The coefficient implies that a one standard deviation in the change in ST per worker is associated with a 0.79 percentage points increase in skill intensity, which represents 38% of the average increase of 2.09 percentage points for this sample.

Table 10.2 reports OLS estimation of the coefficients on equation (5) for two different samples. Column 1 reports the coefficients for the sample with positive spending on technology, and Column 3 reports the coefficients for the full sample, where the zeros were replaced by the minimum value observed in the sample with positive ST . In both cases the coefficient is significant at 1%, being 0.40 in the restricted sample and 0.26 in the full sample. The coefficient in the first sample implies that one standard deviation in spending on technology per worker is associated with 0.71 percentage points increase in skill intensity, which represents 39% of the average increase of 1.83 percentage points. Columns 2 and 4 report estimation of coefficients on equation (4) when initial skill intensity is omitted, in that case the coefficient on spending on

technology per worker is still significant, but smaller, as some firms (high productivity always exporters) that spend a lot on technology had already adopted the high technology.

Table 10.1
Tests of Prediction 5: Changes in Technology and Skill Upgrading
Change in Technology Spending

LHS var.: Change in the share of skilled labor

	(1)	(2)
Change log (ST/L)	0.708 [0.190]***	0.739 [0.188]***
Share of skilled labor ₁₉₉₂		-0.048 [0.015]***
Constant	1.770 [0.216]***	2.647 [0.315]***
Industry dummies	Yes	Yes
Observations	973	973
R-squared	0.15	0.16

Robust standard errors in brackets. * indicates significant at 10%; ** significant at 5%; *** significant at 1%.

Table 10.2
Tests of Prediction 5: Changes in Technology and Skill Upgrading
Level of Technology Spending

LHS var.: Change in the share of skilled labor

	(1)	(2)	(3)	(4)
	Sample with ST>0	Sample with ST>0	Full Sample	Full Sample
Log (ST ₁₉₉₃₋₁₉₉₆ /L ₁₉₉₂)	0.397 [0.115]***	0.262 [0.115]**	0.256 [0.070]***	0.162 [0.068]**
Share of skilled labor ₁₉₉₂	-0.051 [0.013]***		-0.049 [0.012]***	
Constant	2.802 [0.267]***	1.889 [0.176]***	2.696 [0.249]***	1.829 [0.184]***
Industry Dummies	Yes	Yes	Yes	Yes
Observations	1258	1258	1516	1516
R-squared	0.12	0.11	0.11	0.09

Robust standard errors in brackets. * indicates significant at 10%; ** significant at 5%; *** significant at 1%.

7 Conclusion

In this paper I proposed that an inquiry on the causes of rising wage inequality that does not treat technology and trade as competing explanations can give different answers than empirical studies founded in the Hecksher-Ohlin framework. Increases in skill intensity within all sectors and the difficulties for identifying effects of trade on wage inequality through variations in trade policy across sectors are consistent with trade and capital account liberalization being the ultimate cause of widening wage inequality once their effects on technology adoption are taken into account.

I proposed a model where liberalization increases market size and reduces technology adoption costs in all sectors. This change produces heterogeneous responses of firms of different initial productivity levels, and thus differential effects of liberalization at the firm-level provide for a better identification strategy than variation across sectors.

I tested the predictions of this model in the context of the trade and capital account liberalization in the early 1990's in Argentina, that was both profound and unexpected. After liberalization the skill premium started increasing at 7 percentage points per year in the industrial sector, and the equilibrium relative demand of skilled labor increased 17% in 5 years. The increase in the relative demand of skilled labor is not explained by labor reallocations across sectors or firms, but by within-firm skill upgrading.

I found that new entrants in the export market upgraded technology faster than other firms, increasing their spending on technology 43% more after liberalization. These firms were not more skill-intensive than non-exporters prior to liberalization, but

upgraded skill 1.75 times faster in the 5 years after liberalization. These differential effects on the firms that were most affected by liberalization suggest that it had a strong impact on technology upgrading. The finding that firms that upgraded technology faster also increased skill intensity faster, where one standard deviation in the change in spending of technology explains 38% of the average increase in skill intensity, suggests that trade can have a strong impact on skill upgrading through its effects on technology adoption.

Some open questions remain. First, I would like to investigate the effects of FDI on technology adoption and skill upgrading further. I found that foreign-owned firms spend more in technology and are more skill-intensive, and proposed better access to credit as an explanation. I would like to investigate this channel further, modeling the foreign investment decision explicitly to obtain more precise predictions that I can test using information on the share of foreign ownership and the sources of financing technology upgrading available in the survey.

Second, I would like to study the channels through which trade affects technology upgrading and skill upgrading in more detail. I would like to investigate whether technology upgrades were caused by changes in product quality and variety or were aimed at reductions in marginal costs, and whether differences in the purpose of technology changes reported in the survey affect skill upgrading differently. Verhoogen (2004) proposes a model where opening up to trade with more developed countries increases exports of high quality goods in developing countries, the production of which requires paying higher wages to skilled workers. I would like to investigate whether quality upgrading also induces changes towards more skill-biased technologies, and if it

occurs in firms that export to developed countries, while firms that export to countries of similar development only increase market size and adopt less skilled-biased technologies. In this case, there would be differential effects of trade on technology and skill upgrading when opening up to trade with more developed countries, or countries of a similar level of development. In the case of Argentina this investigation could contribute to the debate on whether joining the Free Trade Area of the Americas (FTAA) or expanding MERCOSUR to other countries of a similar level of development.

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Appendix A

Technology and Exporting Decisions when $\varphi_x^{LH} < \varphi_{dx}^L$

The sorting of firms into exporting and technology adoption depends on the ordering of two other cutoffs φ_{dx}^H and φ_d^{LH} defined by:

$$\pi_x^H(\varphi) > \pi_d^H(\varphi) \Leftrightarrow \varphi > \varphi_{dx}^H = \left[\frac{f_x}{\tau^{1-\sigma} E^*(P^* \rho)^{\sigma-1} \frac{1}{\sigma} (c_H^{1-\sigma})} \right]^{\frac{1}{\sigma-1}}$$

$$\pi_d^H(\varphi) > \pi_d^L(\varphi) \Leftrightarrow \varphi > \varphi_d^{LH} = \left[\frac{(f_H - f_L)}{E(P\rho)^{\sigma-1} \frac{1}{\sigma} (c_H^{1-\sigma} - c_L^{1-\sigma})} \right]^{\frac{1}{\sigma-1}}$$

Note that Proposition 1 implies that $\varphi_{dx}^H < \varphi_{dx}^L$, and Proposition 2 implies that

$\varphi_x^{LH} < \varphi_d^{LH}$. Then there are two relevant cases:

1. $\varphi_x^{LH} < \varphi_d^{LH} < \varphi_{dx}^H < \varphi_{dx}^L$

In this case, the exporting and technology adoption decisions are characterized as follows:

If $\varphi < \varphi_d^{LH}$: the firm serves only the domestic market and uses technology L.

If $\varphi_d^{LH} < \varphi < \varphi_{dx}^H$: the firm serves only the domestic market and uses technology

H.

If $\varphi_{dx}^H < \varphi$: the firm exports and uses technology H.

2. $\varphi_x^{LH} < \varphi_d^{LH} \quad \varphi_{dx}^H < \varphi_{dx}^L \quad \varphi_{dx}^H < \varphi_d^{LH}$

In this case, there are two possible configurations described as 2.a and 2.b:

$$2.a \ \varphi_x^{LH} < \varphi_{dx}^H < \varphi_d^{LH} < \varphi_{dx}^L \quad \text{or} \quad \varphi_x^{LH} < \varphi_{dx}^H < \varphi_{dx}^L < \varphi_d^{LH}$$

Under these orderings of cutoffs the exporting and technology adoption decisions are characterized as follows:

- If $\varphi < \varphi_{dx}^H$: the firm serves only the domestic market and uses technology L.
- If $\varphi_{dx}^H < \varphi$: the firm exports and uses technology H.

$$2.b \ \varphi_{dx}^H < \varphi_x^{LH} < \varphi_d^{LH} < \varphi_{dx}^L \quad \text{or} \quad \varphi_{dx}^H < \varphi_x^{LH} < \varphi_{dx}^L < \varphi_d^{LH}$$

Under these orderings of cutoffs the exporting and technology adoption decisions are characterized as follows:

- If $\varphi < \varphi_x^{LH}$: the firm serves only the domestic market and uses technology L.
- If $\varphi_x^{LH} < \varphi$: the firm exports and uses technology H.

Then in case 1 there are firms serving only the domestic market and using the low technology, domestic firms using the high technology and exporters using the high technology. In case 2 there are only domestic firms using the low technology and exporters using the high technology. In none of these cases there are exporters using the low technology.